DECISION MAKING ACROSS PROSPECTIVE GAINS AND LOSSES: DIVERGENCE OF RISK AND VALUE PROCESSING AND CONVERGENCE FOR VALUE-TO-UTILITY TRANSFORMATIONS

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DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

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Table of Contents

Summary

The goal of the field of decision neuroscience is to understand the neural mechanisms that underlie individual choice behavior. The present dissertation investigates the behavioral and neural basis of how individuals modulate subjective value across monetary gains and losses in response to outcome uncertainty. Economic decision making in the gains and losses domains were investigated at both the behavioral and the neural levels. In the first three studies, separable effects of aging, sleep deprivation, and cognitive fatigue were found in gains and losses decision making. Contrary to dominant economic theory, we also found no significant correlations between gains and losses risk preferences, suggesting independence. In the fourth behavioral study, this independence was confirmed using an intermixed-trial design. The fifth study, using fMRI, examined the neural mechanism of the value-to-utility transformation, the process for converting from count to worth. We demonstrated, with independent within-study replication, that the dorsal anterior midcingulate cortex (daMCC) contains the information necessary to perform the value-to-utility transformation across both gains and losses. Overall, these findings demonstrate that there are both dissociable and overlapping cognitive/neural mechanisms across domains such as the overlapping executive processes (e.g. the value-to-utility transformation) and differential valuative processes (e.g. the encoding of value signal) in the gains and losses domains.

List of Tables

List of Figures

List of Abbreviations

aMCC	Anterior Midcingulate Cortex
BART	Balloon Analogue Risk Task
BIS	Baratt Impulsive Scale
CGT	Cambridge Gambling Task
CV	Chosen Value
daMCC	Dorsal Anterior Midcingulate Cortex
dmPFC	Dorsomedial Prefrontal Cortex
dlPFC	Dorsolateral Prefrontal Cortex
EV	Expected Value
fMRI	Functional Magnetic Resonance Imaging
GDS	Geriatric Depression Scale
GLM	General Linear Model
IFG	Inferior Frontal Gyrus
IGT	Iowa Gambling Task
IRB	Institutional Review Board
MMSE	Mini Mental State Examination
NAcc	Nucleus Accumbens
OA	Older adults
PFC	Prefrontal Cortex
PPI	Psychophysiological Interaction
PVT	Pyschomotor Vigilance Test
pWIN	Probability of Winning
RAVLT	Rey Auditory Verbal Learning Test

rCV	Relative Chosen Value
rEV	Relative Expected Value
ROI	Region of Interest
RW	Rested Wakefulness
RSME	Rating Scale Mental Effort
SCR	Skin Conductance Response
SD	Standard Deviation
SDMT	Symbol Digit Modalities Test
SEM	Standard Error of Mean
SV	Subjective Value
SVM	Support Vector Machine
TMT	Trail Making Test
TSD	Total Sleep Deprivation
vmPFC	Ventromedial Prefrontal Cortex
YA	Younger Adults

Chapter 1: Introduction

Decision making is an integral part of our life. Humans make decisions everyday throughout the entire lifetime. Interestingly, clear individual differences can be seen in the way people make choices and it is the goal of the field of decision neuroscience to understand the neural mechanisms that underlie individual choice behavior (Glimcher & Rustichini, 2004; Smith & Huettel, 2010). As decision making involves complex cognitive processes, investigations are done in both the behavioral and neural levels, typically by investigating specific variables from a decision making phenomenon of interest and looking for their neural correlates in the brain.

This dissertation focuses on understanding the behavioral and neural basis of how individuals modulate subjective value by looking at risky monetary decision making across the gains and losses domains. Overall, three research topics were examined: 1) the behavioral effects of state modulations on decision making, 2) the behavioral differences and relationships between decision making for gains and for losses, and 3) the neural mechanism of the value-to-utility transformation.

Behavioral studies investigating risky decision making

Clear individual differences can be seen in the way individuals make choices depending on their subjective value and preferences. The subjective value or utility, which is the worth of an option to an individual, can be modulated by individual's preference depending on the context, for example the ownership of the item of choice, the uncertainty of the outcome of the decision, and the effort and time needed to obtain the choice.

One of the most common variables that has been extensively studied in the topic of risky decision making is risk preference. For decision making under risk, individuals are on average risk averse (preferring smaller certain rewards to larger uncertain rewards) when making decisions about potential gains, but risk seeking (preferring larger uncertain rewards to smaller certain rewards) when faced with decisions about potential losses (Laury & Holt, 2000; Kahneman & Tversky, 1979; 1984; Schoemaker, 1990). This suggests that under uncertainty, i.e. the condition of having imperfect knowledge about which potential outcome each available option will lead to (Knight, 1921), people tend to diminish the subjective value (utility) of gains compared to their actual objective value, but tend to enhance the subjective value (utility) of losses compared to their actual objective value.

Apart from differences in how people perceive the value of gains and losses, choice behavior may also be affected by the different preferences in the strategy they use to guide the decision making process. For example, individuals can take into consideration the amount of potential gains or losses (Rabin, 2000; Tversky & Kahneman, 1992), the outcomes of prior choices (Thaler & Johnson, 1990), or the probabilities of the prospect (Kuhberger, Schulte-Mecklenback, & Perner, 1999). With the presence of known probabilities in risky choices, individuals may consider their choices based on the computed expected value of each option or just based on simple heuristics like the likelihood of outcome (Tversky, 1969; Ernst & Paulus, 2005; see Padoa-Schioppa, 2015 and Piantadosi & Hayden, 2015 for further discussion).

Risk preference and subjective value modulation

Subjective value modulation can be clearly demonstrated in individual responses to risky gambles. For instance, while the expected value of a lottery ticket may be $10 (such as a 50% chance of winning $20 and a 50% chance of $0) different individuals would be willing to pay different prices for the ticket, depending on the degree and the direction of their subjective valuation. Should they be risk averse, they would diminish the expected utility of the ticket (value > utility), while a risk seeking person would enhance the subjective utility of the ticket (value < utility). In other words, increase risk aversion reduces the utility of the gamble, while increase risk seeking enhances the utility of the gamble.

The study of subjective valuation is extremely important as it is the integration between sub-components of our executive function (the top-down system that manages other cognitive processes in our brain that facilitates the attainment of goal directed behavior) and the affective/valuative system (Phelps et al., 2014) . One metaphor to describe the role of the executive function is the role of the conductor in an orchestra (as illustrated by Brown, 2006). The conductor directs, modulates and coordinates the musicians to produce good music (e.g. the pace, the volume of the sound, and when to start and stop the playing). Just like the conductor of an orchestra who needs to enhance and diminish the loudness of the music, subjective value modulation involves the enhancement and diminishment of objective value. The process of value diminishment likely involves cognitive inhibition by the executive function. For example, when someone exercises self-control for not choosing a tasty but unhealthy food (Hare et al., 2009) or when a drug user resists drugs on the basis of better long term outcome (Bechara, 2005), they may be diminishing the subjective value of the desired objective through cognitive inhibition to suppress the urge to obtain those objects. The process of value enhancement may not necessarily involve cognitive inhibition. Only one study has looked at the value enhancing and the value diminishing process, showing modulated value signal in the lateral prefrontal cortex in the gains domain of risky decision making (Tobler et al., 2009). No study has directly investigated the neural mechanism of the value-to-utility transformation, and whether the same mechanism is performed in both the gains and losses domains.

Functional studies investigating risky decision making

Existing studies investigating neural correlates of decision making have identified several common brain regions related to decision making, with most having overlapping functions associated with executive control and the affective system (Smith & Huettel, 2010). Some brain areas that are commonly reported in decision making studies are the ventromedial prefrontal cortex (vmPFC) and ventral striatum (VS), which have activation found to be correlated with subjective value, constituting the valuation system (Yacubian et al., 2006; Breiter et al., 2007; Tobler et al., 2007; Rolls, McCabe & Redoute, 2008; Levy et al., 2011; Lim et al., 2011; Bartra, McGuire & Kable, 2013); the posterior parietal and lateral prefrontal cortices, related to contextual control including stimuli information (Huettel et al., 2006; Weber & Huettel, 2008); the anterior insula (AI) and inferior frontal gyrus (IFG), associated with inhibitory control including the avoidance of risk (Kuhnen &

Knutson, 2005; Christopoulus et al., 2009); and the dorsomedial prefrontal cortex (dmPFC), suggested to play a central role in cognitive control during decision making (Venkatraman et al., 2009; Xue et al., 2009) (see Figure 1.1).

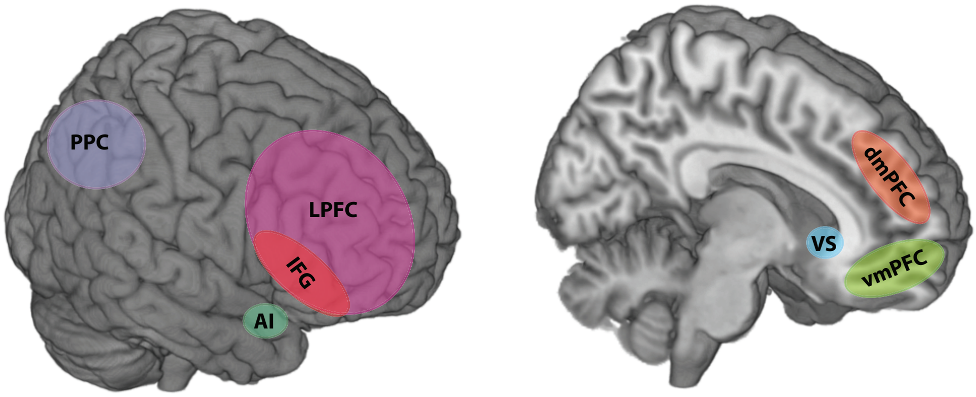

Figure 1.1. Common brain areas associated to decision making. AI = anterior insula; dmPFC = dorsomedial prefrontal cortex; IFG = inferior frontal gyrus (IFG); LPFC = lateral prefrontal cortex; PPC = posterior parietal cortex; vmPFC = ventromedial prefrontal cortex; VS = ventral striatum.

Some prior studies have also investigated the different brain activations in different states. For example, 1) decrease activation in the striatum and insula during loss anticipation in healthy older adults (Samanez-Larkin et al., 2007), 2) increase activation for expected gains in the nucleus accumbens and decrease activation for losses in the insular and orbitofrontal cortices during sleep deprivation (Venkatraman et al., 2007), 3) increase activation in the vmPFC and VS in adolescence resulting in more risk taking behavior (Van Leijenhorst et al., 2010), and 4) decrease activation in the prefrontal cortex during decision making in substance users resulting in impaired decisions (Tanabe et al., 2007). These studies are often helpful to improve our understanding about their roles in decision making

Besides differences in brain activation modulated by different states, some other studies have also reported brain regions showing differential responses to gains and losses. Interestingly, most of these brain regions are associated to the affective system. For examples, 1) amygdala lesions impair decisions regarding gains but not losses (Weller et al., 2007), 2) vmPFC lesions result in more risk averse behavior for gains, but more risk seeking behavior for losses (Pujara et al., 2015), 3) brain regions involved in decision making show differential activation to gains and losses, such as in the vmPFC (including regions of the orbital frontal cortex), amygdala, ventral striatum and hippocampus (Elliott et al., 2000; Yacubian et al., 2006; Luking & Barch, 2013), and 4) gains but not losses value signal in the vmPFC (Bartra et al., 2013; Clithero & Rangel, 2014). These studies show that gains and losses decision making do not involve the exact same neural mechanisms although many of them may be overlapping.

Research aim

The aim of this dissertation is to investigate the behavioral patterns and neural mechanisms of decision making, especially to understand the neural mechanism of subjective valuation. We specifically focused on risky decision making to look at how risk modulates subjective value.

This dissertation aims to answer three specific research questions:

1) How are gains and losses monetary decision making, differentially altered by different kinds of states?

Subjective value modulation (measured using risk preference) and the use of relevant information to make choices in aging, sleep deprivation and cognitive fatigue were behaviorally investigated. No study has contrasted the effects of these states on economic decision making within the same task to see whether they would produce the same effects. By answering this research question, we would be able to infer whether these different states affect overlapping or non-overlapping cognitive/neural processes across gains and losses decision making by seeing whether they have similar or dissociable effects.

Prior studies have reported that aging, sleep deprivation and cognitive fatigue produce deleterious effect on executive function and vigilance (Berardi, Parasuraman, & Haxby, 2001; Pang et al., 2006; Persson et al., 2007; Lim & Dinges, 2008). Furthermore, aging and sleep deprivation both have been reported to attenuate responses to losses in the insula and brain regions related to subjective value (Venkatraman et al., 2007; Samanez-Larkin et al., 2007), while no prior study has investigated the effects of cognitive fatigue on risky decision making. Therefore, we can expect to find similar effects across all three states on economic decision making, especially for aging and sleep deprivation.

2) What are the differences and relationships between gains and losses decision making in terms of subjective value modulation and the use of choice information?

In order to answer this research question, risk preference and the strategy of utilizing choice information in gains and losses decision making were contrasted. Although gains and losses differ mainly in sign, numerous studies have demonstrated robust decision making differences across gains and losses. As mentioned earlier, in terms of risk preference, there is a robust finding in the literature that individuals are on average risk averse in the gains domain, but risk seeking in the losses domain (Laury & Holt, 2000; Kahneman & Tversky, 1979; 1984; Schoemaker, 1990). Moreover, decisions that are framed as losses have been suggested to exert more cognitive effort (for review see Baumiester et al., 2001), along with longer reaction time (Payne et al., 1993) and eye-fixation time (Kuo, Hsu & Day, 2009). The difference in the amount of effort exerted may be reflected in the amount and type of choice information used to make decisions.

3) How does the brain perform the value-to-utility transformation for gains and for losses and how are these brain areas functionally connected to other brain areas involved in decision making?

No study has directly investigated the neural mechanism of the value-to-utility transformation. Additionally, here we also tested to see whether the same mechanism is performed in both the gains and losses domains. Without investigating both the gains and losses domains, our understanding about the neural correlates of decision making will be greatly limited because our value scale should range from negative (losses) values to positive (gains) values, and unspecific (e.g. by only studying the gains value signal, we cannot dissociate between neural correlates of value and attention).

Research significance

Overall, this research will facilitate our understanding of human decision making and executive function. As many debilitating disorders have been associated with impairments in decision making and executive function, such as in the autism spectrum and attention deficit hyperactivity disorders (Coolidge, Thede & Young, 2000; Allman et al., 2005; Happe et al., 2006), schizophrenia and bipolar disorder (Kurnianigsih et al., 2011) and addictions (Hester & Garavan, 2004; Bechara, 2005), further research will not only facilitate our understanding of decision making, but also facilitate the production of treatments and interventions for these disorders.

Overview of the studies

This dissertation consists of five separate studies. The first three studies sought to examine how monetary decision making are differentially altered by different kinds of states: aging (Chapter 2), total sleep deprivation (Chapter 3), and cognitive fatigue (Chapter 4). In the first study (Chapter 2), we looked at behavioral differences between younger and older adults in uncertainty preferences and choice strategies (the influence of trial factors on choices). We looked at and quantified uncertainty preferences from both types of uncertainty, risk (when the probabilities of possible outcomes are known) and ambiguity (when the probabilities of possible outcomes are not well defined) (Knight, 1921; Ellsberg 1961; Camerer & Weber 1992), but focused mainly on risk.

In the second study (Chapter 3), we did a within-subject comparison in younger adults to examine how one night of total sleep deprivation alters uncertainty preferences (risk and ambiguity), choice strategies, and the degree of loss aversion. In the third study (Chapter 4), we did a between-subject comparison in younger adults to examine how cognitive fatigue (induced through 60 to 90 minutes of taxing cognitive engagement) alters uncertainty preferences (risk and ambiguity) and choice strategies.

The fourth study (Chapter 5) sought to examine the differences and relationships between behavioral measures of gains and losses decision making. In the three prior studies (Chapter 2-4), we found no relationship between gains and losses risk preferences , differing from the expectation of theoretical reflection effect. We tested specifically the correlation between gains and losses risk preferences and how well cross-domain risk preferences could inform individual choice behavior using a gains and losses intermixed-trial design. Classical behavioral models considered differences between gains and losses risk preferences were simply reflection across domain – people are risk averse for gains and risk seeking for losses, with risk preferences across domains considered negatively correlated and are the result of the same underlying process. In this chapter, we show clear independence between risk preferences when considering prospective gains and prospective losses.

The fifth study (Chapter 6) sought to localize the neural instantiation of the value-to-utility transformation – how objective value (count) are translated into subjective value (utility/worth), which is a core component in decision making. We made use of the dissociability of the gains and losses uncertainty preferences reported in previous chapters to construct a within-task replication (separate investigation in the gains and losses domains). The results in this study suggest that the information necessary to perform the value-to-utility transformation is encoded in the dorsal anterior midcingulate cortex (daMCC, also referred to as the dmPFC). Furthermore, functional connectivity analyses identified brain regions that may input contextual information to set the value-to-utility transformation (through positive connections with the inferior frontal cortex) and receive modulation of encoded values (through negative connections with the nucleus accumbens). The patterns of results were consistent across both the gains and losses domains. This study is the first study to specifically identify the neural mechanisms of the value-to-utility transformation.

In the next chapter (Chapter 7), we integrate the interpretations of all our studies into a general discussion. The consistency across findings and further interpretation about the studies' findings are discussed in more detail in this chapter. The similarities and differences between the gains and losses domains in terms of risk preference, the encoding of value signal and the value-to-utility transformation are specifically discussed.

In the final chapter (Chapter 8), we discuss future research directions building from the results that we have obtained. We proposed a new research study that is a continuation of the behavioral and functional magnetic resonance imaging (fMRI) studies reported in this dissertation. The background and rationale, aims, methods, preliminary findings and potential implications of this proposed future study are discussed.

Overview of the research materials and methods

Our approach was to first study choice behavior to quantify the relationships and differences between the decision components (uncertainty preference to quantify subjective value modulation, choice strategy to quantify the degree of reliance on trial information) and then use fMRI to investigate the neural correlates of these decision components. As our main focus was on risky decision making, our main task was an incentive-compatible risky decision task that was slightly modified across our studies (from Stanton et al., 2009). Within each trial, participants chose between two options, an option with certain monetary amount or a gamble option. Across trials there were five different values of the certain option ([$3, $4, $5, $6, $7] for gains and [-$3, -$4, -$5, -$6, -$7]) for losses, three different probability of winning the gamble option (25%, 50%, 75%), a set of relative expected values (ranges from 0.1 to 4.0 but varies slightly across studies), and a possible zero outcome for the gamble option. The task was used to behaviorally quantify individual's risk preferences and the amount of choice information used.

Risk preference. Risk preferences were measured using two approaches: 1) psychophysical indifference point analysis (risk premium), and 2) power function analysis. The risk premium metric directly measures the degree and direction an individual modulates the value of a gamble due to uncertainty of the outcome. For example, in order to be indifferent between the gamble and certain options, a risk premium of 1 means that the expected value of the gamble option must be one time more than the value of the certain option and a risk premium of 2 means that the expected value of the gamble option must be two times more than the value of the certain option. On the other hand, the power function risk preference measures the curvature of the utility function and shows the degree of the diminishing weight of marginal utility (as previously used in Levy et al., 2010 and Tymula et al., 2012, 2011;

see Material and Methods in each study for detailed information).

In the first three studies (Chapter 2-4), our preferred measure of risk preference was the risk premium metric. While the power function metric assumes that risk preference is due to diminishing weight of marginal utility, the risk premium metric assumes a linear relationship between value and utility across the range of possible outcomes in our task design (~\$100). The assumption of linearity is based on the belief that the rate of diminishing weight of marginal utility to produce non-negligible nonlinearities within our range of outcomes would result in implausible preferences for much larger outcome values (Rabin, 2000). However, in the fMRI study, we opted to use the power function metric for our main covariate analyses, as it has been more commonly used in the literature and accepted by other researchers.

We show that the risk premium and power function measures of risk preference are highly isometric and functionally can be used interchangeably. Across all our studies, we found strong correlations ($r > |.55|$, $p < .0001$) between the risk premium and the power function measures and consistent pattern of results. We also compare these metrics in post-hoc analyses in Chapter 6 (using fMRI), and demonstrate conserved results across these two metrics for capturing individual response to uncertainty.

Choice Strategy. The choice strategy metric measures the influence of trial factors on choices for each individual. Choice strategy is quantified through the use of linear regressions. Analyses were conducted separately within the gains and losses domains through independent linear regressions to determine the influence of two factors on each participant choices: 1) the relative expected value of the options (rEV), and 2) the probability of winning (pWIN) the gamble option.

The R-squared value of each factor quantifies the proportion of individual's choice variance (across trials within domain) accounted for by each factor. Therefore a high R-squared value for rEV or pWIN indicate that choices were influenced by that trial information (for example, an individual who accepts all gambles with a 75% chance of winning would have a high R-squared pWIN value, and an individual who accepts gambles with an rEV equal or higher than 1.25 would have a high R-squared rEV value), whereas a low R-squared value would indicate that choices were more likely to be based on other factors or were made randomly. It is important to note that the pWIN and rEV R-squared values do not share any variances as they are independent to each other (the inter-trial correlation between rEV and pWIN is always zero).

We also note that the use of linear regression to quantify proportion of choice variance is imperfect – the relationship between the trial factors, rEV and pWIN, on choice is not always closer to a linear fit, sometimes it is closer to a sigmoidal fit. To test the robustness of our choice strategy metric, we also tested some of our data using logistic regressions. We found very high correlations between the R-squared values from the logistic (with McFadden's pseudo R-squared) and linear models (all $r > |.70|$, $p < .0001$). Furthermore, in another study, it was empirically shown that linear and logistic regressions gave nearly identical outcomes when the dependent variable was a dichotomy (Hellevik, 2009), concurring with our findings.

Using the risky decision task for the fMRI study. The risky decision task was also used to investigate the neural encoding of value and the neural mechanism of the value-to-utility transformation. Since our trials were designed based on a set of predetermined rEVs (we had 9 levels in the fMRI study), we were able to visualize the actual neural encoding of the rEV formulation in the vmPFC by looking at the degree of brain activation for each rEV level. Armed with the behaviorally derived quantification of each individual's value-to-utility transformation expressed in their risk preference value, we sought the neural instantiation by covarying the value on each trial (constructed from the rEV regressors) against each individual's risk preference. Moreover, as we consistently found no significant correlation between gains and losses risk preferences in our previous studies, we were able to leverage on this to construct a within-study replication for our fMRI study. We replicated the findings in the gains domain to the losses domain by repeating the same between-subject covariate analysis using losses risk preferences in the losses trials. Through this replication, we were able to investigate whether the brain areas involved in the value-to-utility transformation in the gains and losses domains overlap with each other.

The absence of correlation between gains and losses risk preferences is an extremely crucial component in this study, as it allows us to dissociate the value-to-utility transformation processes from other cognitive processes, such as inter-subject level of decision conflict. If risk preferences between the gains and losses domains were strongly correlated to each other, an alternative interpretation of the result would be that neural correlates of risk preferences are associated with individual's level of decision conflict. For example, if risk preferences were correlated to each other, those people who were further away from risk neutrality in both domains would have higher levels of decision conflict than those people who were more risk neutral in both domains. Due to the absence of correlation between gains and losses risk preferences, we note explicitly that our results cannot be due to choice difficulty or decision conflict, as the value-to-utility functions are orthogonal to choice difficulty.

Chapter 2: Differential modulation of risky decision making by aging across prospective gains and losses[1,2]

This is the first of three studies examining modulation of economic decision making by differential state modulations. As the three different state modulations (aging, sleep deprivation, cognitive fatigue) have all been reported to have deleterious effects on executive function and vigilance, we were interested to see whether they would show similar effects on economic decision making. We specifically examined differences in behavioral measures of uncertainty preferences and choice strategy across the gains and losses domains.

In this chapter we investigate how aging alters economic decision making. In the next two chapters, using the same task and analytic approaches, we investigate sleep deprivation (Chapter 3) and cognitive fatigue (Chapter 4). The key advantage that we had that was different from previous studies in the literature was that we were able to compare the three different state modulations in the exact same tasks and that we were able to dissociate between uncertainty preferences and choice strategy.

[1] This paper has been previously published as: Kurnianingsih YA, Sim SKY, Chee MWL and Mullette-Gillman OA (2015) Aging and loss decision making: increased risk aversion and decreased use of maximizing information, with correlated rationality and value maximization. Front. Hum. Neurosci. 9:280. doi: 10.3389/fnhum.2015.00280

[2] Contributions: OAMG designed the study. SSKY coordinated data collection. YAK and OAMG analyzed and interpreted the data. YAK and OAMG wrote the manuscript with comments from CMWL.

Abstract

In this chapter, we investigated how adult aging specifically alters economic decision-making, focusing on examining alterations in uncertainty preferences (willingness to gamble) and choice strategies (what gamble information influences choices) within both the gains and losses domains. Within each domain, participants chose between certain monetary outcomes and gambles with uncertain outcomes. We examined preferences by quantifying how uncertainty modulates choice behavior as if altering the subjective valuation of gambles. We explored age-related preferences for two types of uncertainty, risk and ambiguity. Additionally, we explored how aging may alter what information participants utilize to make their choices by comparing the relative utilization of maximizing and satisficing information types through a choice strategy metric. Maximizing information was the ratio of the expected value of the two options, while satisficing information was the probability of winning.

We found age-related alterations of economic preferences within the losses domain, but no alterations within the gains domain. Older adults (OA; 61 to 80 years old) were significantly more uncertainty averse for both risky and ambiguous choices. OA also exhibited choice strategies with decreased use of maximizing information. Within OA, we found a significant correlation between risk preferences and choice strategy. This linkage between preferences and strategy appears to derive from a convergence to risk neutrality driven by greater use of the effortful maximizing strategy. As utility maximization and value maximization intersect at risk neutrality, this result

suggests that OA are exhibiting a relationship between enhanced rationality and enhanced value maximization. While there was variability in economic decision-making measures within OA, these individual differences were unrelated to variability within examined measures of cognitive ability. Our results demonstrate that aging alters economic decision-making for losses through changes in both individual preferences and the strategies individuals employ.

Introduction

Aging has been suggested to result in alterations in numerous cognitive processes, but it is unclear what specific alterations in economic decision making may take place. Understanding age-related alterations of economic decision-making is important, as elderly persons are often less financially resilient and often considered more likely to be targets of consumer fraud (Lee & Soberon-Ferrer, 1997; Castle et al., 2012; Ross et al., 2014). In this study, we specifically test whether economic decision making is altered in a healthy sample of older adults (OA), through tasks that control for dissociable processes (such as learning or memory effects).

At the most general cognitive levels, aging is associated with decreased processing speed (Salthouse, 2000) and deficits in a range of cognitive processes, including inhibition (Lustig et al., 2007), executive functions (Goh et al., 2012), episodic memory (Shing et al., 2008), and reward learning (Mell et al., 2005). These changes in cognitive abilities may in turn affect economic decision-making, such as the propensity to invest (Christelis et al., 2010; Korniotis & Kumar, 2011).

Prior studies utilizing decision making tasks have suggested alterations across a range of tasks, including the Iowa Gambling Task (IGT) (Denburg et al., 2005; Wood et al., 2005; Fein et al., 2007; Zamarian et al., 2008; Denburg et al., 2009; Baena et al., 2010; Carvalho et al., 2012), the Gambling Task (Kovalchik et al., 2005), Balloon Analogue Risk Task (BART) (Henninger et al., 2010; Rolison et al., 2012) and the Cambridge Gambling Task (CGT) (Deakin et al., 2004; Henninger et al., 2010). However, it is unclear whether such studies reflect specific alterations in economic decision making, as these tasks feature outcome resolution at the end of each trial. As aging has been found to impact reward learning (Mell et al., 2005; Eppinger et al., 2011), it is unclear if the observed behavioral changes are merely an extension of age-related decline in learning or if they truly reflect altered preferences or strategies (see Mata et al., 2011; Worthy et al., 2011). The former account is supported by some (Henninger et al., 2010; Boyle et al., 2011) but not other studies (Anderson et al., 2013).

Here, we examined how economic decision-making may be specifically altered in relatively healthy OA, focusing on two aspects of economic decision-making: uncertainty preferences (risk and ambiguity) and choice strategies.

Uncertainty preferences are a measure of how an individual responds to the unknown future resolution of a probabilistic option (i.e., a gamble). Uncertainty can be described as being of two types, as risk when the probabilities of possible outcomes are known or can be estimated, or as ambiguity when the probabilities of possible outcomes are not well defined (Knight, 1921; Ellsberg 1961; Camerer & Weber 1992).

Uncertainty preferences differ depending on whether individuals are facing potential gains or losses (Prospect Theory, Kahneman & Tversky, 1979). Given the ubiquity of losses in real-world decisions, it is important to understand how aging may differentially impact decision making across both the gains and losses domains. Across both the gains and losses domains, prior behavioral studies investigating age-related modulation of uncertainty preferences have resulted in inconsistent findings. In the gains domain, while some studies found OA to be more risk averse than younger adults (YA) (Lauriola & Levin, 2001a; Albert & Duffy, 2012; Mather et al, 2012; Tymula et al., 2013), others did not show age-related effects (Mikels & Reed, 2009; Sproten et al., 2010). Inconsistencies have also been observed in the losses domain with some studies suggesting that OA are more risk averse (Mikels & Reed, 2009), and others suggesting that they are more risk seeking (Lauriola & Levin, 2001a; Mather et al, 2012). Only two studies have investigated age-related alterations of ambiguity preferences, with one suggesting that OA are less ambiguity averse than YA in the gains domain (Sproten et al., 2010) and the other finding no alterations (Tymula et al., 2013). Only one prior study has investigated age-related alteration of ambiguity preferences in the losses domain, finding OA were slightly more risk averse than YA (Tymula et al., 2013). Neural evidence further suggests that we may anticipate an asymmetry in age-related modulation across the gains and losses domains. Samanez-Larkin and colleagues (2007) found reduced responsiveness in OA to anticipated monetary losses within striatal regions, while showing similar modulations to YA in the gains domain.

Beyond preferences, decision making is also dependent on the strategy one employs to utilize available information to reach their decision. For example, when choosing between two gamble options, one can simply consider the probability of winning for each option, or one can calculate and compare the expected value of each. In a potentially-related domain, previous studies have reported that OA tend to use simpler and less demanding strategies for decision making involving probabilities (Kim et al., 2005;

Rafaely et al., 2006). However, no prior study has investigated age-related differences in strategy use in monetary decision making.

In the present study, we examined how aging effects uncertainty preferences and choice strategies by contrasting relatively healthy OA with YA. To evaluate age-related differences, participants engaged in two incentive-compatible decision tasks (one with gains and one with losses), from which we computed their uncertainty preferences (risk and ambiguity) and quantified the choice strategy they employed to reach their decisions. Our *a priori* hypotheses were that: 1) healthy aging would result in no alteration of uncertainty preference in the gains domain, 2) OA would be less risk- and ambiguity-seeking in the losses domain, and 3) OA would present diminished choice strategies across both the gains and losses domains.

Materials and Methods

Participants

Data for the YA group were collected from 62 undergraduate students studying at the National University of Singapore (NUS) (24 males; age range = 19 – 26 years, age mean ± SD = 21.90 ± 1.69 years). Data for the OA group were collected from 39 cognitively healthy participants of the Singapore Longitudinal Brain Aging Study (Chee et al., 2009). These participants were screened, to exclude any of the following: 1) history of significant vascular events (i.e., myocardial infarction, stroke or peripheral vascular disease), 2) history of malignant neoplasia of any form, 3) history of cardiac, lung, liver, or kidney failure, 4) active or inadequately treated thyroid disease, 5) active neurological or psychiatric conditions, 6) a history of head trauma with loss of consciousness, 7) a Mini-Mental State Examination (MMSE) (Folstein et al., 1975) score <26, 8) a 15-point modified-Geriatric Depression Screening Scale (GDS) (Sheikh & Yesavage, 1986), or 9) a history of illicit substance use.

All participants provided informed consent under a protocol approved by the National University of Singapore Institutional Review Board.

Two OA were excluded from analyses due to gross task performance issues in the monetary decision tasks, resulting in a final sample of 37 OA (22 females; age range of 61 to 80 years, mean ± SD = 68.66 ± 5.15 years). The demographics of the final sample of YA and OA participants are listed in Table 2.1. During their sessions, participants also performed additional behavioral tasks and surveys unrelated to this study.

Table 2.1. Participant demographics

Younger Adults	N = 62
Female, %	61.29
Age, years	22 ± 1.7
Older Adults	N = 37
Female, %	56.76
Age, years	69 ± 5.5
Education, years	12.1 ± 3.4
MMSE	28.1 ± 1.4
GDS	.97 ± 1.38

Abbreviations: MMSE, Mini mental state examination; GDS, Geriatric depression screening

Experimental design

Data was collected as part of a larger-ongoing study. For the measures included in this report, participants underwent multiple measures of cognitive ability and performed two monetary decision making tasks (the first for the gains domain and the second for the losses domain).

Measuring Cognitive ability in OA

Cognitive ability in OA was evaluated across five domains: 1) attention and working memory, 2) verbal memory, 3) visuospatial memory, 4) executive functioning, and 5) processing speed. Attention and working memory was assessed with the Digit Span (Wechsler, 1997) and a computerized version of a Spatial Span task. Verbal memory was evaluated using Rey Auditory Verbal Learning Test (RAVLT) (Lezak et al., 2004). Visuospatial memory was evaluated using a Visual Paired Associate test. Executive functioning was evaluated using a Categorical Verbal Fluency test (using categories of animals, vegetables, and fruits), the Design Fluency test (Delis et al., 2001), and the Trail Making Test B (Reitan & Wolfson, 1985). Processing speed was assessed with the Trail Making Test A (Reitan & Wolfson, 1985) and the Symbol-Digit Modalities Test (SDMT) (Smith, 1991). To limit the number of comparisons, individual test scores were standardized (z-transformation) and combined within each categorical domain. We examined whether these cognitive domains are related to economic measures by correlating the composite scores from each of the five cognitive domains with our uncertainty preference and choice strategy metrics. The significance of these correlations was adjusted using Bonferroni correction for multiple comparisons with a threshold of $p < .01$ (i.e., correcting for the five cognitive domains).

Uncertainty Preference Tasks

Uncertainty preferences (risk and ambiguity) were gathered through two monetary decision making tasks (see Figure 2.1), with each task oriented towards either the gains or losses domains. All participants performed the uncertainty-gains task followed by the uncertainty-losses task. On each trial of each task, participants chose between a certain option and a gamble option. Participants were informed that reimbursement would be determined at the end of the experiment based on random selection and resolution of one trial from each task. No resolutions were provided before the end of the entire experiment to eliminate alterations of preferences and choice strategies due to inter-trial learning from trial outcomes. Data collection and analyses were achieved using MATLAB (Mathworks, Natick, MA) with Psychophysics Toolbox (Brainard, 1997) for trial presentation.

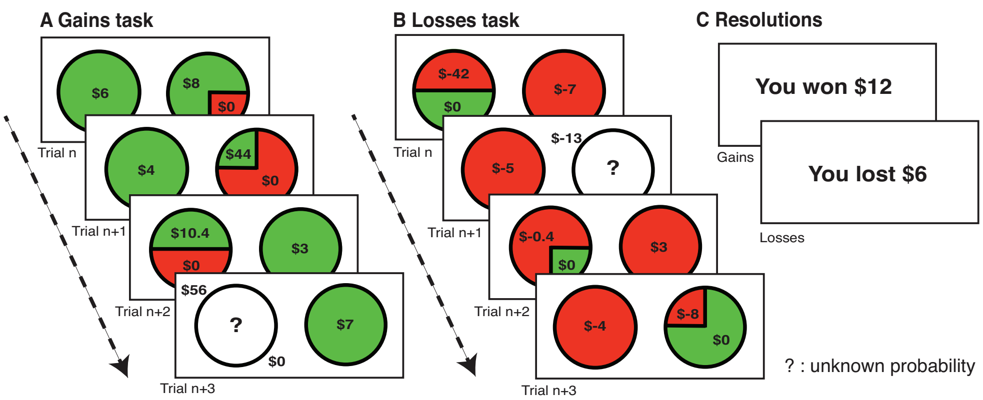

Figure 2.1. Task timelines. Participants performed two monetary decision-making tasks. One in the (A) gains domain (rewards) followed by a (B) losses domain version. In each trial, participants were asked to choose between a certain or a gamble option, with unconstrained response time. (C) Participants' payments were based on random selection and resolution of one trial from each task, selected and resolved at the end of the entire experiment.

The uncertainty-gains task (Stanton et al., 2011), consisted of 165 trials, in which the participant chose between a certain option and a gamble option, which was either risky or ambiguous. For both gamble types, losses always resulted in $0 outcome. For risky gambles, there were five certain options ($3, $4, $5, $6, and $7), three probabilities of winning (25%, 50%, and 75%) and the value of the potential win ranged from $2 to $98, dependent upon the ratio of the expected value of the gamble to the certain option (relative expected value (rEV) or EV_G/ V_c) for that trial. The trial matrix was constructed based on examining nine different rEVs (0.5, 1.0, 1.3, 1.6, 1.9, 2.2, 2.5, 3.0, and 3.5). With three probabilities of winning and the 5 different certain values, there were 15 trials for each level of rEV. For ambiguous gambles, six rEVs were examined (0.5, 1.0, 2.0, 3.0, 4.0, and 6.0), calculated using an assumed 50% probability of winning (by the law of large numbers). This resulted in 5 trials at each rEV, given the 5 values of the certain option.

The uncertainty-losses task consisted of 200 trials, closely mirroring the uncertainty-gains task, save for shifting the valence and adjusting the rEV values to allow for an anticipated increase in risk-seeking preferences (Kahneman & Tversky, 1979). There were five certain loss options (-$3, -$4, -$5, -$6, and -$7,) with ten examined rEVs (0.1, 0.3, 0.5, 0.8, 1.0, 1.3, 1.5, 2.0, 3.0, and 4.0); this adjusted range resulted in potential gamble losses ranging from -$0.4 to -$112. With three probabilities of winning (25%, 50%, and 75%) and the 5 different certain values, there were 15 trials for each level of rEV, as in the gains domain. These ten rEV values were also examined for ambiguous gambles, calculated using an assumed 50% probability of winning. This resulted in 5 ambiguous trials at each rEV, given the 5 values of the certain option.

Quantifying uncertainty preferences

Within each task, we quantified risk and ambiguity preferences by utilizing individual's choice functions to find the ratio of the expected values of the gamble to the certain option at which participants were indifferent between the two. Each preference value is an expression of the degree and direction in which the participant's choice behavior suggests they are modulating the subjective expected value of the gamble due to the outcome being unknown.

For each participant, four preference values were calculated (risk and ambiguity for the gains and losses domains) through psychometric indifference point analyses (Stanton et al., 2011). For each, a choice function was constructed based on the proportion of gamble options selected at each rEV. Examples of choice functions for individual participants within the gains domain are shown in Figure 2.2A and for the losses domains in Figure 2.2B. The indifference point was defined as the first point at which the projected choice function crossed 50%. We subtracted 1 from this indifference value to generate a 'premium' value. As such, the premium measures the degree to which the participant subjectively modifies the absolute expected value of a gamble due to outcome uncertainty. A zero premium reflects no change, a positive premium shows diminished valuation, and a negative premium indicates enhanced valuation. These calculations were performed separately for risk and ambiguity in each domain, gains and losses, resulting in four independent premium values.

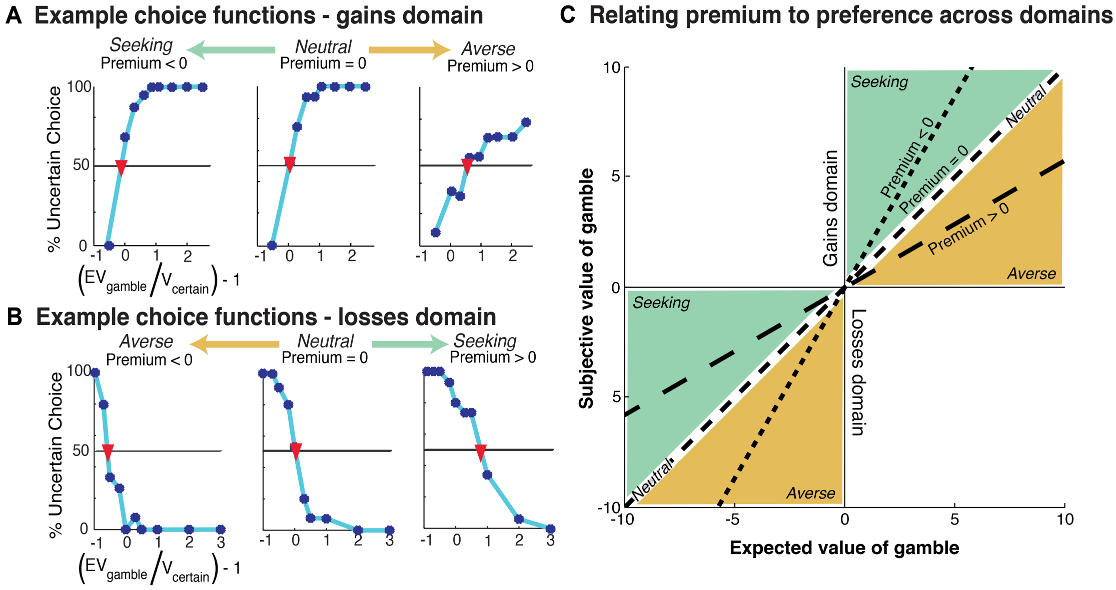

Figure 2.2. Example participant choice functions. (A) Gains domain, the range of risk preferences across participants is represented from risk seeking (left) to risk averse (right). The indifference point of each choice function is shown with a red inverted-triangle. Risk premium is defined as the value on the '(EV_G / V_c) -1' (x-axis) at this indifferent point. (B) Losses domain, the range of risk preferences is represented from risk averse (left) to risk seeking (right). (C) Relationship between premium metric and risk preference. Premium value corresponds to the slope of the line. Note that, as the premium value modulates the absolute expected value of the gamble, its relationship to preference (averse or seeking) is inverted between the gains and losses domains – e.g., positive premium values reflect risk-averse preferences in the gains domain and risk-seeking in the losses domain.

On a technical note, our quantification of uncertainty preferences assumes a linear relationship between value and utility across the range of possible outcomes (~$100 in each task). While non-linearities may be evident when dealing with much larger sums (i.e., the difference in marginal utility for a dollar when you have fifty or when you have one million), the required rate of diminishing marginal utility to produce non-negligible nonlinearities within a $100 range would result in highly untenable preferences when dealing with any large economic choice (Rabin, 2000).

As the premium metric quantifies the relative alteration of the absolute expected value of the gamble, its relation to preference (aversion and seeking) is inverted over the gains and losses domains (see Figure 2.2C). A positive premium in the gains domain indicates diminished absolute valuation of the gamble, which is also diminished valuation relative to the certain option. In the losses domain the same positive premium value still indicates diminished absolute valuation of the gamble, however, this is a relative increase in valuation compared to the certain option as the expected value of the gamble becomes less negative. As such, the interpretation of premium values into preference requires a reversal across domains (see Figure 2.2C). Therefore, in the gains domain, positive premium values show aversion and negative premium values indicate seeking, while in the losses domain, positive premium values indicate seeking and negative premium values indicate aversion. Neutrality corresponds to zero premium values in both domains.

We note that in a prior study using the uncertainty-gains task in a larger sample (N~300, Stanton et al., 2011), our psychometric premium values were highly correlated (correlations over |.60|) with power function preference values (Prelec 1998). We note now, similar high correlations between these measures of risk preference within the losses domain (Risk losses $r(93) = -.71$, $p < .0001$; Ambiguity losses $r(92) = -.77$, $p < .0001$). For empirical reasons, due to the specific design of this task, we prefer the psychometric premium metric over the power-function measure (for a full description of these reasons, please see Stanton et al. (2009), Supplemental).

A small number of participants had choice functions that did not cross the indifference point (50% acceptance of gamble), preventing the psychometric determination of their premium values. Our data cannot resolve whether such participants were simply not performing the task correctly or if such participants had extreme preferences (we cannot differentiate between a participant who employed a strict heuristic (such as ‘always choose the certain/gamble option’) from one that considered the options but always selected the certain/gamble option because they are truly that averse/seeking to the gamble). This resulted in the exclusion of variable numbers of participants across the uncertainty metrics and domains (risk gains: 10 OA and 10 YA; risk losses: 2 OA and 2 YA; ambiguity gains: 14 OA and 23 YA; and ambiguity losses: 1 OA and 3 YA). Importantly, there were no significant differences in the proportions of participants excluded across the OA and YA for any cell (risk gains: χ^2 (1, N = 99) = 1.71, p = .19; risk losses: χ^2 (1, N = 99) .284, p = .59; ambiguity gains: χ^2 (1, N = 99) .005, p = .94; and ambiguity losses: χ^2 (1, N = 99) .27, p = .60).

Quantifying choice strategy

We examined whether aging altered what information participants relied upon to make their decisions through the use of a choice strategy metric. For each participant, we performed four independent linear regressions, two for each domain. Each regression determined the influence of a specific informational factor on choice in risk trials. We examined two factors: 1) the relative expected value of the option (rEV), and 2) the probability of winning in the gamble option (pWIN). Importantly, our task designs fully-orthogonalize the pWIN and rEV factors (i.e., in each task the correlation of the values of pWIN and rEV across trials is zero).

The R-squared value derived from each regression is a direct expression of the maximal amount of an individual’s choice variance (across trials) that can be accounted for by the examined factor (for examples, see Figure 2.4A to 2.4D). We directly contrasted utilization of these two competing trial-information sources by subtracting the R-squares of the rEV and pWIN factors. This results in our *choice strategy* metric (see Figure 2.4E to 2.4H), which directly measures how much more each participants' choice behavior can be explained by the cognitively demanding calculation of the relative expected value of the options than by simple utilization of the visually-available probability of winning the gamble.

This choice strategy metric is positive when participants utilize the rEV information more, negative when they focus on the pWIN information, and zero when they use the two equally. For example, a participant whose decisions were solely based on the value of pWIN (e.g., accepting all gambles with a 75% chance of winning) would have a high pWIN R-squared value, a low rEV R-squared value, and therefore a highly negative choice strategy. Similarly, a participant whose choices were determined by comparing the expected values of the gambles would have a high R-squared value for rEV and low pWIN, resulting in a positive choice strategy value. Participants were considered to be 'maximizing' when they used the rEV information more and 'satisficing' when they used the pWIN information more, as focusing on pWIN allows for decisions through extremely simple heuristics ('how much of the gamble pie is green?') requiring little cognitive effort, while utilization of the rEV information maximizes long-run outcomes but requires several layers of effortful cognitive calculation.

We note that we opted to focus on the rEV and pWIN factors due to task design. While rEV and pWIN are orthogonal, other trial factors do not share this feature. For example, in the gains task the absolute value of the possible win is highly correlated to both the rEV and pWIN factors (rEV: $r(133) = .604, p < .0001$; pWIN: $r(133) = -.576, p < .0001$), with similar correlations in the losses task.

Relationship between risk preference and choice strategy

As we found significant age-related effects for both uncertainty preferences and choice strategies within the losses domain, we looked for a possible interaction by examining the correlation between these metrics within each age group.

Results

Cognitively intact older sample

Our OA participants were cognitively unimpaired (MMSE ≥ 26), exhibiting psychometric test scores comparable to healthy participants studied elsewhere (Table 2.2, comparing Trail-Making Test A, SDMT from Hsieh & Tori, 2007; Trail Making Test A and B from Tombaugh, 2003; Digit Span from Hedden et al., 2002; RAVLT from Davis & Klebe, 2001).

Table 2.2. Cognitive measures in OA

Cognitive Domain	Psychometric Test	Mean ± SD
Attention and working memory	Digit Span forward	10.0 ± 2.3
	Digit Span backward	7.2 ± 1.9
	Spatial Span forward	7.5 ± 1.5
	Spatial Span backward	6.9 ± 1.5
Processing speed	SDMT (written)	44.6 ± 10.0
	SDMT (oral)	51.0 ± 12.0
	TMT A (s)	40.5 ± 14.0
Verbal memory	RAVLT	
	Sums of trials 1-5	51.4 ± 7.5
	Immediate recall list A	4.8 ± 1.6
	Delayed recall list A	10.9 ± 2.4
	Recognition list A	14.1 ± 1.9
Visuospatial memory	Visual paired associates	
	Sums of trials 1-4	16.9 ± 5.8
	Delayed recall	5.1 ± 2.0
Executive functioning	Categorical fluency	43.2 ± 7.3
	Design fluency	27.1 ± 7.5
	TMT B (s)	92.2 ± 41.8

Abbreviations: SDMT, Symbol digit modalities test; TMT, Trail Making Test; RAVLT, Rey auditory verbal learning test.

Relationship between economic measures and cognitive ability in OA

To examine whether differences in cognitive ability within our OA sample may alter economic preferences, we examined the relationships between our economic metrics and cognitive ability within our OA sample. Cognitive ability was quantified across five cognitive domains − attention and working memory, verbal memory, visuospatial memory, executive functioning, and processing speed (Table 2.3). To compare each of these five domains to each economic metric, we set a Bonferroni corrected significance threshold of $p < .01$ (correcting for the five examined cognitive domains), followed strictly as this was an ancillary component of the study. No significant correlations were found between performance on these cognitive domains and our uncertainty preferences (risk or ambiguity) or choice strategies.

Table 2.3. Relationships between decision making metrics and cognitive performance in OA

	Gains		Losses	
Cognitive Domain	Premium	Strategy	Premium	Strategy
Attention and working memory	r(25) = -.03 p = .94	r(31) = .28 p = .12	r(33) = .43 p = .010	r(35) = .02 p = .89
Verbal memory	r(25) = -.10 p = .62	r(31) = -.20 p = .27	r(33) = .08 p = .64	r(35) = -.08 p = .63
Visuospatial memory	r(25) = -.06 p = .77	r(31) = .01 p = .95	r(33) = .29 p = .10	r(35) = -.14 p = .40
Executive functioning	r(25) = -.01 p = .95	r(31) = .13 p = .47	r(33) = -.18 p = .31	r(35) = .14 p = .41
Processing speed	r(25) = -.09 p = .65	r(31) = .18 p = .32	r(33) = .28 p = .11	r(35) = .22 p = .20

To account for multiple comparisons across the five cognitive domains, a Bonferroni corrected significance threshold of $p < .01$ was applied.

Effects of aging on risk and ambiguity preferences

To examine whether aging alters risk and ambiguity preferences, we contrasted our YA and OA samples, with comparisons listed in Table 2.4 and shown in Figure 2.3. Within the gains domain, YA and OA were similarly risk averse (mean ± SD YA = .64 ± .66, OA = .55 ± .61, between group difference $t(77) < 1$, p = n.s.). Within the losses domain, we identified significant age-related differences, with YA risk seeking (mean ± SD = .22 ± .59) and OA risk averse (mean ± SD = -.17 ± .31, between group difference $t(93) = 3.662$, $p < .001$).

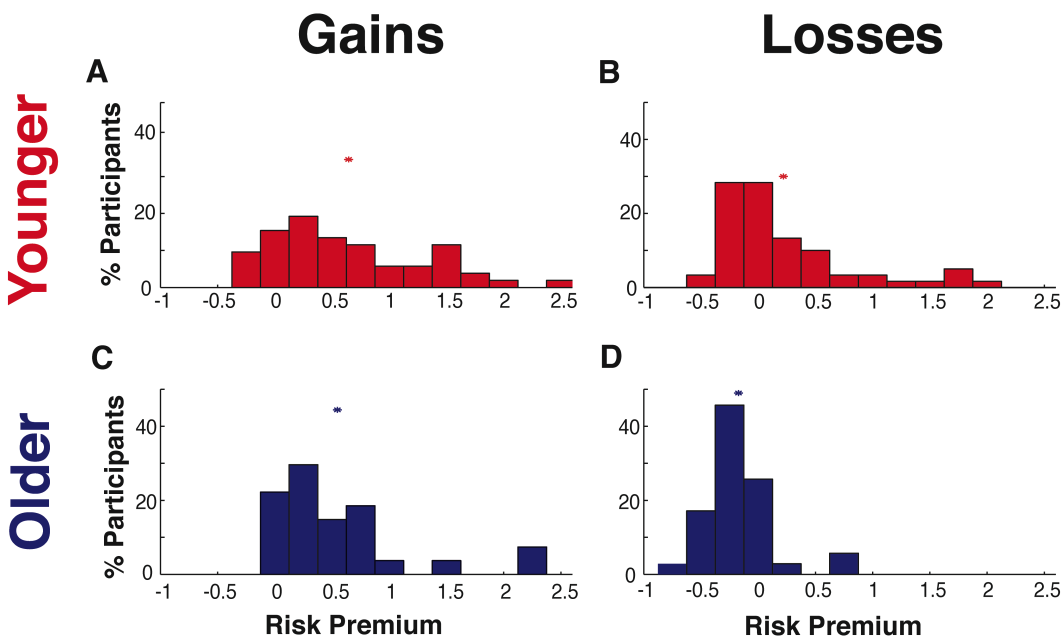

Figure 2.3. Risk preferences. Distribution of individual risk premium values for (A) YA in the gains domain, (B) YA in the losses domain, (C) OA in the gains domain, and (D) OA in the losses domain. The "*" shows the mean of each distribution.

A similar pattern of age-related effects was also found for ambiguity preferences (Table 2.4). In the gains domain, participants in both age groups were equally ambiguity averse (mean ± SD YA = 1.54 ± 1.46, OA = 1.46 ± 1.04, between group difference $t(60) < 1$, n.s.). While in the losses domain, YA were ambiguity seeking (mean ± SD = .24 ± .77) and OA were ambiguity averse (mean ± SD = -.19 ± .30; $t(93) = 3.14$, $p = .002$). Calculation of Cohen's *d* indicated moderate to large effect sizes (Cohen, 1988) for age-related differences in both risk and ambiguity preferences within the losses domain (Cohen's *d*, risk = .78, ambiguity = .66).

Table 2.4. Comparison of economic measures between YA and OA

	YA *Mean ± SD*	**OA** *Mean ± SD*	**YA vs. OA** *p-value*
Gains Domain			
Uncertainty Premium			
Risk	.65 ± .66	.55 ± .61	.52
Ambiguity	1.54 ± 1.46	1.46 ± 1.04	.81
Risk × Ambiguity	r(35) = .33, **p = .043**	r(19) = .55, **p = .009**	
Information Strategies			
Choice strategy	.16 ± .24	.12 ± .22	.43
r^2 rEV	.26 ± .14	.21 ± .16	.15
r^2 pWIN	.10 ± .12	.09 ± .11	.75
Response Time (s)			
Risk	1.55 ± .61	2.49 ± .90	**< .0001**
Ambiguity	1.35 ± .52	2.34 ± .83	
	p = .046	p = .48	
Losses Domain			
Uncertainty Premium			
Risk	.22 ± .59	-.17 ± .31	**< .001**
Ambiguity	.24 ± .78	-.18 ± .40	**.002**
Risk × Ambiguity	r(56) = .77, **p < .0001**	r(33) = .68, **p < .0001**	
Information Strategies			
Choice strategy	.38 ± .15	.31± .16	.052
r^2 rEV	.40 ± .13	.35 ± .13	.058
r^2 pWIN	.03 ± .04	.04 ± .05	.21
Response Time (s)			
Risk	1.74 ± 0.51	3.17 ± 1.27	**< .0001**
Ambiguity	1.69 ± 0.46	3.37 ± 1.25	
	p = .57	p = .49	

Abbreviations: rEV, Relative Expected Value; pWIN, Probability of Winning. Overall participants responded slower in the losses tasks than in the gains task with significant difference in OA ($p < .01$) and marginally significant difference in YA ($p = .068$).

We found correlations between risk and ambiguity preferences within the gains domain (YA: $r(35) = .34$, $p = .043$; OA: $r(19) = .55$, $p = .009$), concurring with a recent study (Lauriola & Levin, 2001b). We extend this finding, showing that risk and ambiguity preferences are also correlated within the losses domain (YA: $r(56) = .80$, $p < .0001$; OA: $r(33) = .68$, $p < .0001$).

Risk preferences across the gains and losses domains were not significantly correlated within either age group (all $r < |.08|$, p = n.s.). Similarly, ambiguity preferences across domains were uncorrelated in YA ($r(35) = -.11$, p = n.s.). However, in OA there was a significant negative correlation between ambiguity preferences across the gains and losses domains ($r(20) = -.46$, $p = .032$). Given the inverse relationship between the premium metric and preferences across domains, this negative correlation shows a positive relationship in OA between ambiguity aversion for gains and for losses.

A potential concern in interpreting the lack of found differences for gains risk preferences between OA and YA could be that highly risk averse participants were 'cut-off' by our task design and analyses, which set a ceiling measurable risk premium value of 2.5. This is extremely unlikely, as demonstrated by estimating the likelihood of finding values outside of our measurable range, based upon the observed risk premium values in the remainder of each of our samples and the normal distribution. For YA, the edge is 2.9 standard deviations from the mean, which indicates that approximately 99.5% of YA should have risk preference values within our measureable range. Similarly, for OA the edge is 3.3 standard deviations from the mean, indicating that approximately 99.9% of participants should have measurable risk premium values. In other words, based upon the means and variance of our participants with viable risk preference values, we anticipate the presence of fewer than 1 participant with preferences extreme enough to not fall within our measureable range. We note that while an adaptive task design would avoid this potential concern by fitting trials to individuals, it would also produce additional concerns such as trial order effects.

Differences in choice strategy across the gains and losses domains

We examined whether aging altered what information participants relied upon to make their decisions through the use of our choice strategy metric. Choice strategy was determined, within each domain, through linear regressions to determine the maximal influence (expressed through R-squared values) of the rEV and pWIN trial-by-trial information on individual choice behavior. These values were determined separately within each of the gains and losses domains across our YA and OA samples (Figure 2.4A to 2.4D).

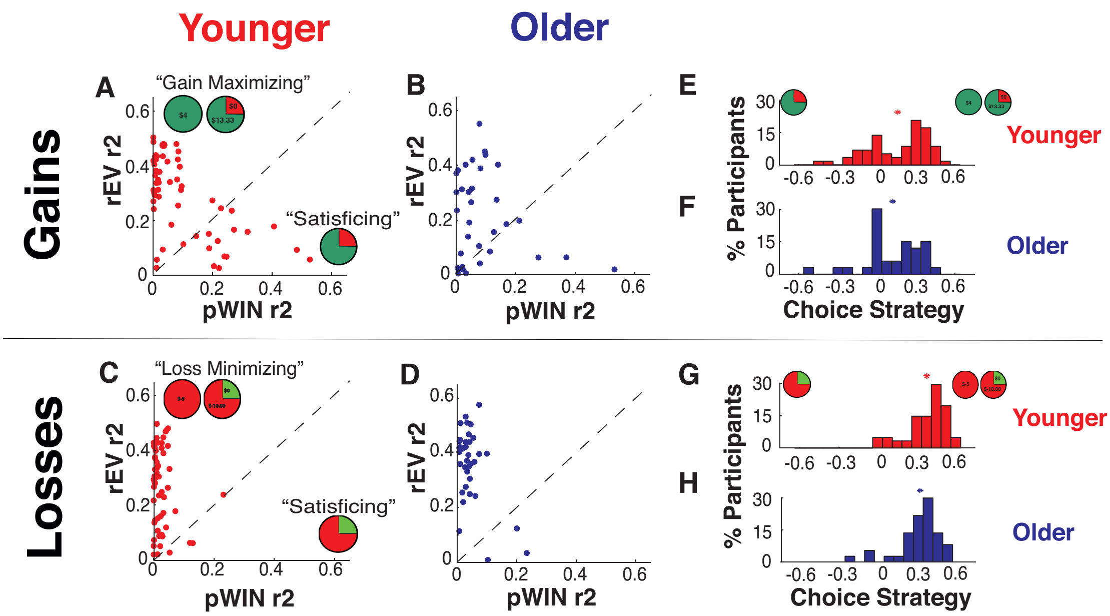

Figure 2.4. Choice strategy – utilization of trial information. Relationship of independent R-squared values of rEV and pWIN on trial-by-trial choice behavior for (A) YA in the gains domain, (B) OA in the gains domain, (C) YA in the losses domain, and (D) OA in the losses domain. Distributions of choice strategy metric (difference between R-squares of rEV and pWIN) for (E) YA in the gains domain, (F) OA in the gains domain, (G) YA in the losses domain, and (H) OA in the losses domain. The "*" shows the mean of each distribution.

Within both the YA and OA groups, we observed significantly higher choice strategies in the losses domain than in the gains domain (YA: $t(117) = 6.00$, $p < .0001$; OA: $t(68) = 4.23$, $p < .0001$) with large effect sizes in both groups (Cohen's d, YA = 1.10, OA = 1.00) (Table 2.4 and Figures 2.4G and 2.4H). As the choice strategy metric is a combination of two factors, we also examine the effects of aging on these factors individually, revealing that the differences were driven by alterations to both components - increased use of the relative expected value (rEV) information (YA: $t(60) = 8.45$, $p < .0001$, $d = 1.06$; OA: $t(34) = 5.13$, $p < .0001$, $d = .94$), along with decreased use of the probability of winning (pWIN) information (YA: $t(56) = 4.62$, $p < .0001$, $d = 0.82$; OA: $t(32) = 2.23$, $p = .033$, $d = .64$). A significant correlation between individual choice strategies across the gains and losses domains was present for YA ($r(55) = .42$, $p = .001$), but absent for OA ($r(31) = .20$, p = n.s.).

Effects of aging on choice strategy

Examining for age-related differences in choice strategy, we found no differences within the gains domain (mean ± SD YA: .16 ± .24, OA: .12 ± .22, $t(89) < 1$, n.s.) (Table 2.4 and Figures 2.4E and 2.4F).

Examining for age-related differences within the losses domain, we found that OA exhibited lower choice strategies than YA (mean ± SD YA: .38 ± .15, OA: .31 ± .16, $t(96) = 1.97$, $p = .052$, Cohen's $d = .41$) (Figures 2.4G and 2.4H). As this change in the composite strategy metric could be driven by either decreased use of rEV information or enhanced use of pWIN information, we examined each component individually. OA showed marginally significant lower use of rEV information (mean ± SD rEV r^2 values YA: .40 ± .13, OA: .35 ± .13, between group difference $t(97) = 1.92$, $p = .058$, Cohen's $d = .40$), without alteration in the use of pWIN information (mean ± SD pWIN r^2 values YA: .03 ± .04, OA: .04 ± .04, between group difference $t(96) = 1.27$, $p = .21$, $d = .27$).

Relationship between risk preference and choice strategy within OA

Given the observed alterations of OA in both risk preferences and choice strategies within the losses domain, we looked for interactions between these metrics (Figure 2.5). We excluded one OA from this analysis, as his/her risk preference and choice strategy interaction was a strong outlier (> 4.95 SD). OA exhibited a highly significant correlation between risk preference and choice strategy in the losses domain (r(32) = .77, p < .0001), such that the closer their risk premium was to zero, the higher their choice strategy. In other words, the greater their reliance on the maximizing information, the more risk neutral their risk preference was. This relationship was absent in YA (r(57) = -.11, p = n.s.). Importantly, such a relationship in OA is not due to our task design or metrics, as evidenced by the absence of such a correlation within YA.

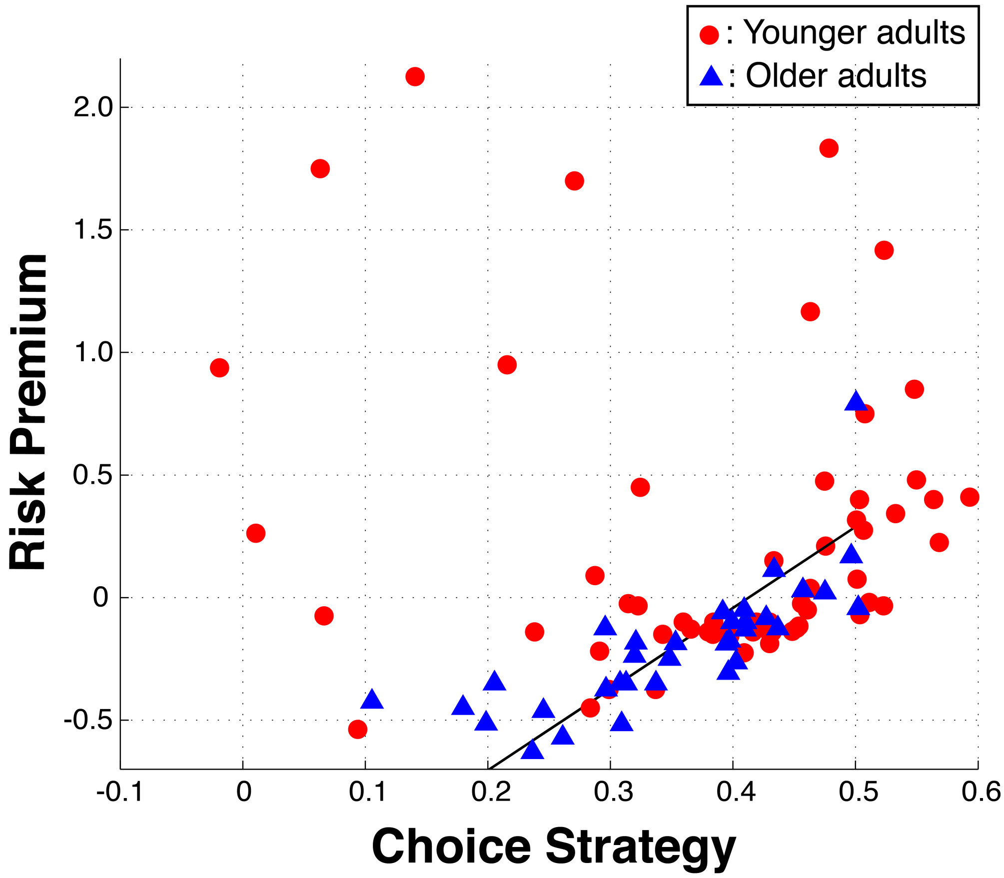

Figure 2.5. Interaction between risk preferences and choice strategies in the losses domain. Within older adults, a positive correlation between risk premium and choice strategy was identified, such that increasing use of the rEV information (maximizing) results in more risk neutral preferences (increased 'rationality'). The included black line is the total least square line for the older adults.

Discussion

We investigated the effects of aging on economic decision-making, focusing on alterations of risk preferences and choice strategies within both the gains and losses domains, contrasting cognitively healthy OA with YA. OA were significantly more risk and ambiguity averse in the losses domain, but were not significantly different from YA within the gains domain. OA also made significantly less use of the maximizing choice strategy in the losses domain. Finally, we found a correlation between risk preference and choice strategy such that the more OA utilized maximizing choice strategies, the more risk neutral (or 'rational') their preferences.

OA are more risk averse for losses

OA were significantly more uncertainty averse in the losses domain, but were not significantly different from YA within the gains domain. YA demonstrated the classic pattern of being risk averse for gains and risk seeking for losses (Kahneman & Tversky, 1979). Contrastingly, OA were risk averse across both the gains and losses domains.

Given that OA have less time to recover from financial catastrophe, they are typically advised to shift their retirement savings away from risky investments, (Jagannathan & Kocherlakota, 1996). The preference differences we found between YA and OA matches this advice. Our finding also expands upon a study by Ebner and colleagues (2006), who found OA to be generally oriented towards prevention of losses while YA focused on pursuing gains. Our results suggest that such a change can be extended to the domain of monetary decision making and could be the result of enhanced uncertainty aversion for losses, rather than reduced responses to gains.

It is unclear how such age-related alterations in economic risk preferences may generalize to other domains, such as medical or social decision making (Weber et al., 2002). In fact, while risk aversion may be beneficial in specific circumstances, an overall increase in risk aversion would not be beneficial in all situations. Good decision making is derived from the ability to tailor our preferences to the specific context and goals of the choice.

We note that our risk preference metric, the risk premium, is not the result of a specific theoretical model, but is simply a zero-centered transform of the psychometric indifference point. A potential pitfall of this empirical formulation of risk preference is that it does not ascribe to any specific theoretical model of risk preference, and therefore is not interpretable specifically in-line with those models. However, a potential advantage of such a model-free metric is that it does not rely on specific theoretical assumptions. For example, expected-utility theory states that the power function risk metric is the result of the diminishing weight of marginal utility, but it is unclear if that is a viable mechanism (Rabin, 2000). Similarly, Prospect Theory suggests that the risk preferences of individuals should be highly correlated across gains and losses (reflection effect), but we find no correlation between risk preferences across domains, concurring with other empirical studies (Cohen et al., 1987; Schoemaker, 1990; Laury & Holt, 2000; Tymula et al., 2013). We note, however, the very strong correlations we find between individual risk premium and power function risk preference measures, indicating that these measures do largely account for the same variance across individuals.

OA have decreased maximizing strategies within the losses domain

Within the gains domain, there was no significant difference between the choice strategies of YA and OA. However, within the losses domain, OA showed lower choice strategies than YA, specifically attributable to lower utilization of the calculated rEV information while maintaining equivalent use of the readily available pWIN information as YA.

A possible explanation for why choice strategy was only altered in the losses domain is that participants may have engaged in more effortful cognitive processing within the losses domain, which may have helped reveal age-related differences. The presence of greater effort is backed by the longer response times in the losses domain (Table 2.4), significant in OA and trending in YA. Further, across both YA and OA, we see higher overall choice strategy and specifically increased utilization of maximizing rEV (not just reduced pWIN), suggesting higher motivation in the losses domain than in the gains domain. Such increases in cognitive effort for loss-related decision making concurs with the standard concept of loss aversion, in which people weigh losses more intensely than gains of the same magnitude (Kahneman & Tversky, 1979). High levels of motivation and cognitive effort have been shown to help reveal age-related effects in complex tasks (McDowd & Craik, 1988; Huxhold et al., 2006). It may be that as aging reduces cognitive capacity, OA adapt by conserving processing resources for highly motivated decisions (Hess et al., 2009). Increased utilization of the maximizing strategy in loss-related decision making may reflect OA consciously choosing to engage in more effortful cognitive processing, but due to limited cognitive resources, OA are unable to match the high performance of YA.

Our finding, that OA made lower use of maximizing information in the losses domain (i.e., lower overall choice strategy metric and specifically decreased rEV), is consistent with prior studies showing that older investors (age 60 and above) are less effective in applying their investment skills due to age-related cognitive decline, even though they have greater investment knowledge and experience than younger investors (Korniotis & Kumar, 2011), although other studies point out that reduced strategy may not necessarily lead to diminished decision quality when simple strategies are viable (Mata et al., 2012).

Correlation between risk preferences and choice strategies in OA

Within the losses domain, the OA who utilized the maximizing rEV information, were more risk neutral. In classical economic utility theory (von Neumann & Morgenstern, 1944) rationality is characterized by utility maximization, which translates into consistent use of risk preferences. Within our sample of OA we see a correlation between preferences and strategy, with maximizing strategy driving risk neutral preferences. This pattern is intriguing for three reasons. Firstly, consistent choice behavior is required for high values on the choice strategy metric. As participants show consistent choices over trials, their behavior can be considered more rational. Secondly, OA, as a group, show convergence on a single preference value, driven by the degree to which they utilize the effortful strategy. In an individual, such consistent application of preferences would result in consistent choice behavior and enhanced rational choice. Thirdly, the specific risk preference value that they converge on is risk neutrality, at which utility maximization converges with value maximization. This suggests that the more OA were motivated and engaged in effortful strategies, the more they focused on maximizing the objective value of their choices. In other words, this specific linkage between risk preferences and strategy suggests that OA are exhibiting a relationship between enhanced rationality and enhanced value maximization. Within YA, we see greater variability in the relationship between risk preference and strategy.

One possible explanation for these differences is that OA have acquired experience over their lifetime about not just *what* information to pay attention to (rEV vs. pWIN), but also *how* to utilize that information. Consistent with our findings, a study conducted by Tentori and colleagues (2001) observed that OA make more 'rational' choices (i.e., less violations of transitivity while selecting hypothetical supermarket discount cards) than YA, suggesting that age-related accumulation of experience leads to greater rational choice. Such wisdom gained through experiences would then produce our found relationship, with higher motivated engagement in the task (i.e., choice strategy) leading to more neutral preferences.

An intriguing question is whether the effects of aging on economic decision-making are non-linear. Middle-aged adults have been suggested to be better economic decision makers than either YA or OA, at least borrowing at lower interest rates and paying fewer fees (Argawal et al., 2007). Potentially, middle-aged adults could have the highest quality decision making as they have the benefits of acquired life experience without cognitive decline. In addition, further studies are needed to understand how performance on lab-based economic tasks translates to real-world economic behaviors (for example, see Li et al., 2015).

Conclusions

Understanding the effects of aging on uncertainty preferences and choice strategies has vital implications for OA. Our study investigated the effects of aging on economic decision-making across both the gains and losses domains, specifically examining alterations in uncertainty preferences, choice strategies, and the interactions of the two. We found clear differences in economic decision-making between YA and OA in the losses domain, with no alterations in the gains domain. Within the losses domain, OA were more risk and ambiguity averse and made less use of maximizing choice strategies. Additionally, we identified a positive effect of aging, a correlation between preference and strategy such that the more engaged a participant was (higher choice strategy), the more rational and value maximizing their behavior was. Our results show that healthy aging results in both positive and negative alterations of economic decision-making preferences and strategies.

Chapter 3: Sleep Deprivation Alters Choice Strategy Without Altering Uncertainty or Loss Aversion Preferences[3,4]

The behavioral findings in Chapter 2 demonstrate how gains and losses economic decision making are differentially altered by aging, with significant alterations found only in the losses domain and not in the gains domain. The study in this chapter sought to examine another state modulation, how 23 hours of total sleep deprivation alters gains and losses economic decision making. As most previous studies looking at the effect of sleep deprivation on decision making focused on the gains domain and reported no alterations, it is interesting to see whether aging and sleep deprivation would show similar effects on decision making.

Abstract

Sleep deprivation is known to alter decision making; however, it is unclear what specific cognitive processes are modified to drive altered choices. In this chapter, we examined how one night of total sleep deprivation (TSD) alters economic decision making. We specifically examined changes in uncertainty preferences dissociably from changes in the strategy with which participants engage with presented choice information. With high test-retest reliability, we show that TSD does not alter uncertainty preferences or loss aversion. Rather, TSD alters the information the participants rely upon to make their choices. Utilizing a choice strategy metric which contrasts the

[3] This paper has been previously published: Mullette-Gillman, O.A., Kurnianingsih, Y. A, & Liu, J.C.J. (2015). Sleep Deprivation Alters Choice Strategy Without Altering Uncertainty or Loss Aversion Preferences. *Frontiers in neuroscience*, *9*, 352.

[4] Contributions: OAMG designed the study. JCJL coordinated data collection. OAMG and YAK analyzed and interpreted the data. OAMG and YAK wrote the manuscript with comments from JCJL.

influence of maximizing and satisficing information on choice behavior, we find that TSD alters the relative reliance on maximizing information and satisficing information, in the gains domain. This alteration is the result of participants both decreasing their reliance on cognitively-complex maximizing information and a concomitant increase in the use of readily-available satisficing information. TSD did not result in a decrease in overall information use in either domain. These results show that sleep deprivation alters decision making by altering the informational strategies that participants employ, without altering their preferences.

Introduction

Total sleep deprivation (TSD) has been found to induce cognitive impairments and reduce the ability to make good decisions and judgments. The effects of TSD on behavior range from alterations of emotional processing (Gujar et al., 2011; Yoo et al., 2007; Killgore et al., 2008; see Kerkhof & Van Dongen, 2010 for review), the desirability of food options (Greer, Goldstein &Walker, 2013), decision making across multiple domains (Harrison & Horne, 2000), and can even increase the likelihood of unethical behavior (Barnes et al., 2011). Recent studies indicate that a large percentage of people regularly suffer from sleep loss globally (Centers for Disease Control and Prevention (CDC), 2011). As such, it is important to understand how TSD influences economic decision making.

TSD has been shown to alter economic decision making across various tasks. For example, sleep-deprived persons have been reported to show an increase in effort discounting (Libedinsky et al., 2013), a shift in behavior from preventing losses to pursuing gains (Venkatraman et al., 2011), a change in the willingness to take risks on the Balloon Analog Risk Task (BART) (Acheson, Richard and Wit, 2007; Killgore, 2007), and poorer performance on the Iowa Gambling Task (IGT) (Killgore et al., 2006). However, it is unclear whether these alterations result from specific alterations of economic preferences, or from alterations of other cognitive aspects of the decision-making process. Accordingly, in this study we sought to specify the effects of sleep deprivation on economic decision making, focusing on preferences (uncertainty and loss aversion) and the information participants utilize to make their decisions (strategy), through a task that controls for potentially-confounding effects on other cognitive domains (such as learning).

Our first goal was to investigate whether sleep deprivation alters uncertainty and loss aversion preferences. Uncertainty preferences quantify how participants alter the valuation of a gamble due to an unknown probabilistic outcome. This can relate to risk (gambles of known probabilities), or ambiguity (gambles with unknown probabilities) (Knight, 1921; Ellsberg 1961; Camerer & Weber, 1992). Empirical evidence has shown that people tend to be risk averse when making decisions about gains and risk seeking when making decisions about losses (Prospect Theory, Kahneman and Tversky, 1979; Kahneman, 2003). Given such clear behavioral differences between gains and losses, it is important to dissociably investigate the gains and losses domains.

The effects of TSD on uncertainty preferences have only been examined in a small number of experimental studies. Most such studies have focused on risk preferences in the gains domain and have found no modulation by TSD (Acheson, Richard & Wit, 2007; Venkatraman et al., 2007; Menz et al., 2012). Utilizing a task that involved altering 5-outcome gambles (involving both possible gains and losses within each trial) Venkatraman and colleagues (2011) suggested increased risk-seeking preference under TSD. One study by McKenna et al. (2007) explored choices to risky and ambiguity options in both the gains and losses domains, finding decreased risk aversion in the gains domain and decreased risk seeking in the losses domain. In this study, we sought to directly test the effects of TSD on risk preferences (independently in the gains and losses domains), while separately assessing alterations of loss aversion or strategy, and avoiding potential confounds (such as learning effects).

Loss aversion refers to the relative weighting of potential gains and losses in decision making, with the average person weighing potential losses approximately twice as strongly as potential gains (Tversky & Kahneman, 1992; Tom et al., 2007). Venkatraman and colleagues (2011) found neural evidence that TSD may alter economic choice behavior from 'defending against losses to seeking increased gains', which would suggest decreased loss aversion. However, they also specifically tested and found no alteration in loss aversion within their task. Here, using a task specifically designed to measure loss aversion (Tom et al., 2007), we directly test the hypothesis that sleep deprivation produces a decrease in loss aversion, either by decreasing the weighting of losses, increasing the weighting of gains, or both.

The final goal of this study was to investigate whether TSD alters the strategy with which participants engage with the available choice information. Our choice strategy metric quantifies the differential utilization of available information in decision making by contrasting between a simple satisficing strategy (the probability of winning the gamble) and a more cognitively-effortful maximizing strategy (determining the relative expected value of each of the available options) (Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015). To date, no study has investigated the effects of TSD on such strategy utilization during economic decision-making. We hypothesized that TSD would result in a decrease in the use of maximizing information (e.g. calculated expected value information) with an increase in the use of readily-available satisficing information (e.g. probability information).

Recent studies have indicated that TSD may result in a decrease in the ability to process available information, including reduced visual short term memory information processing (Chee & Chuah, 2007), limited selective attention (Lim et al., 2010), reduced processing of peripheral information (Kong et al., 2012), and reduced rapid picture processing (Kong et al., 2014). This presents a secondary hypothesis for us to examine with our strategy analyses – whether TSD produces an overall decrease in the use of available information.

In this study, we examined how TSD alters economic preferences and choice strategy using three incentive-compatible decision-making tasks: 1) the gains choice task, 2) the losses choice task, and 3) the loss aversion task. We hypothesized that TSD would not alter uncertainty or loss aversion preferences, but would result in alterations of the information participants relied upon to make their decisions.

Materials and Methods

Subjects

Data were collected from twenty-nine members of the National University of Singapore community (17 males; age range = 19 – 26 years, mean ± SD = 21.66 ± 1.88 years). Participants selected for this study indicated that they: 1) had good habitual sleep (sleep duration of 6.5-9 hours daily, sleeping before 00:30 and waking before 09:00), 2) were not of an extreme chronotype (as assessed by an abbreviated version of the Horne-Öbsterg Morningness-Eveningness questionnaire; Horne and Östberg, 1976), 3) had no history of sleep, neurological, or psychiatric disorders, 4) were nonsmokers, and 5) drank fewer than three caffeinated drinks per day. Additionally, participants' sleep patterns were monitored throughout the duration of the study through the use of wrist actigraphy (Actiwatch, Philips Respironics, USA); only those who evidenced good habitual sleep were included. All participants provided informed consent in compliance with a protocol approved by the National University of Singapore Institutional Review Board.

Study procedure

Participants made three visits to the lab, each scheduled one week apart. In the first visit, participants were briefed about the study protocol, trained on study tasks, and given a wrist actigraph to be worn throughout the study. Participants then completed the rested wakefulness (RW) and total sleep deprivation (TSD) sessions, with session order counterbalanced across participants. All participants indicated that they had not consumed any medication, caffeine, nicotine, or alcohol for at least 24 hours prior to each session.

For the TSD session, participants arrived at the lab at 19:00 the night before the experiment. Throughout the night, participants were monitored to ensure they kept awake and engaged only in sedentary activities. Participants also completed hourly assessments of vigilance (the 10-minute Psychomotor Vigilance Task, PVT; Dinges et al., 1997).

For the RW session, participants arrived at the lab at 20:30 and were given 9 hours of sleep opportunity. Participants performed one assessment of vigilance and of subjective sleepiness upon waking up.

In the morning, our economic tasks began at 10:15 for the RW session, and 7:45 for the TSD session (see Figure 3.1A); as such, the effects described here represent the interaction of circadian and homeostatic factors (Goel et al., 2013). As part of a larger study, participants also completed additional computerized tests, behavioral questionnaires, and functional magnetic resonance imaging sessions (not reported here).

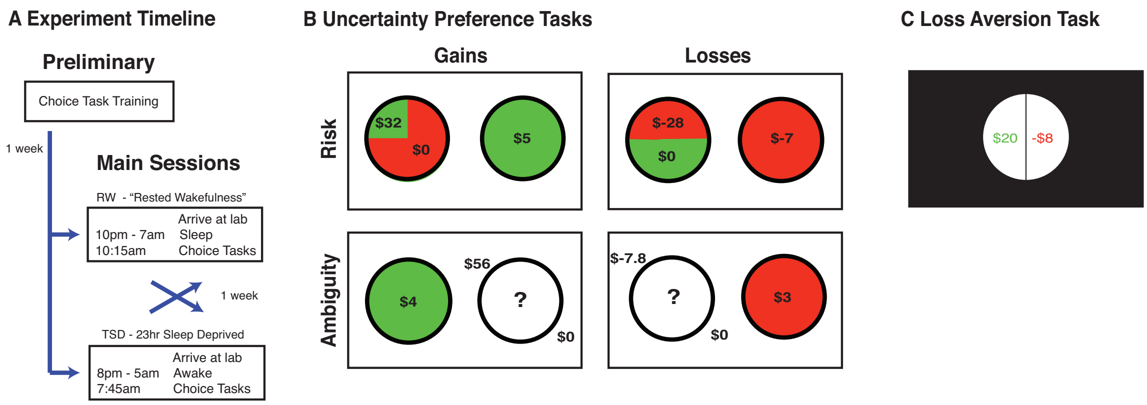

Figure 3.1. Experimental Design. (A) Participants attended 3 sessions, 1 preliminary session followed by 2 main sessions, which were each ~1 week apart. The order of the RW and TSD session was counterbalanced across participants. (B) Example trials for the gains choice task and the losses choice task. (C) Example trial for loss aversion task. For all the monetary decision making tasks, resolution of one trial from each task was given at the end of the experiment to determine participants' payment. No outcome resolutions were given during any tasks until completion of the final experimental session.

All participants completed three tasks in the following order: gains choice task, losses choice task, loss aversion task. At the beginning of the preliminary session, participants were informed that their final monetary payment would be adjusted by $0 to $30 based upon the choices that they make. At the end of the entire experiment, we would randomly select one trial from each of the three tasks from each main session (6 trials in total), resolve their choices, and pay them an unspecified percentage of the total funds they accumulated (which was 33%). Importantly, participants were reminded to treat each trial as the one that mattered, as it could be the one randomly selected and resolved. For the loss aversion task, participants were told they were receiving a $20 endowment (see task description), which was added to their accumulated funds, and helped ensure that participants ended up with a positive final accumulation. No trials were selected, nor gambles resolved, until the conclusion of the entire experiment to eliminate possible alterations of preferences and strategies due to learning effects. Participants were paid in in Singapore dollars.

Experimental design

Uncertainty preference tasks. Uncertainty preference (risk and ambiguity) and choice strategy were evaluated using our gains choice task and losses choice task (Stanton et al., 2011; Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015). Participants performed these two monetary decision tasks, one featuring choices between possible monetary gains and the other between possible monetary losses. On each trial, participants chose between a certain option and a gamble option with varied value and probability of winning (Figure 3.1B). Data collection and analyses were achieved using MATLAB (Mathworks, Natick, MA) with Psychtoolbox (www.psychtoolbox.org).

The gains choice task consisted of 165 trials (see full description in Stanton et al. 2011; Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015 see full trial metrics in Appendix A). On each trial, the participants chose between a certain monetary option (such as $3) and a gamble that was either risky or ambiguous. The 135 risk trials contained a gamble with a known probability of winning a presented value (such as 50% of $8) against a fixed alternative of receiving $0. The 30 ambiguity trials had the same form, except that the gamble had an unknown probability of winning. Risk and ambiguity trials were intermixed and randomized across participants. The matrix of presented risky gambles was constructed from 5 certain gain options {\$3, \$4, \$5, \$6, \$7}, three probabilities of winning {25%, 50%, 75%}, and nine different relative expected values (rEV or the ratio of the expected value of the gamble to the value of the certain option, EV_G/ V_c) which were {0.5, 1.0, 1.3, 1.6, 1.9, 2.2, 2.5, 3.0, 3.5}. Potential win values ranged from \$2 to \$98. For ambiguous gambles, six rEVs were examined {0.5, 1.0, 2.0, 3.0, 4.0, 6.0}, and presented gamble values were calculated based on an assumed 50% probability of winning, resulting in values ranging from \$3 to \$84. For both risky and ambiguous options, a loss would always result in \$0 outcome. Gamble values were rounded to the nearest ten cents for presentation during choices.

The losses choice task consisted of 200 trials, with 150 risk trials and 50 ambiguity trials. The losses choice task was based on the gains choice task, with altered valence and adjusted rEV values. The adjusted set of ten rEVs {0.1, 0.3, 0.5, 0.8, 1.0, 1.3, 1.5, 2.0, 3.0, 4.0} were utilized across both risk and ambiguity trials, resulting in potential losses ranging from -\$0.40 to -\$112.

Quantifying uncertainty preferences. We quantified uncertainty preferences using psychometric indifference point analyses to identify the rEV at which the participant would choose the gamble option 50% of the time, thus indicating indifference between the certain and gamble options. Choice functions were constructed by plotting a continuous function based upon the percentage of accepting the gamble option (y-axis) to each respective assigned rEV (EV_G/ V_c). Examples of choice functions for both domains are shown in Figure 3.2. The choice functions were generally monotonic and the first point where the percentage of accepting the gamble option crossed 50% was defined to be the indifference point. We determined the premium value by subtracting 1 from this indifference point to produce a premium value metric with zero indicative of risk neutrality. These analyses were conducted separately for risk and ambiguity and across gains and losses, resulting in four independent uncertainty premium values for each participant.

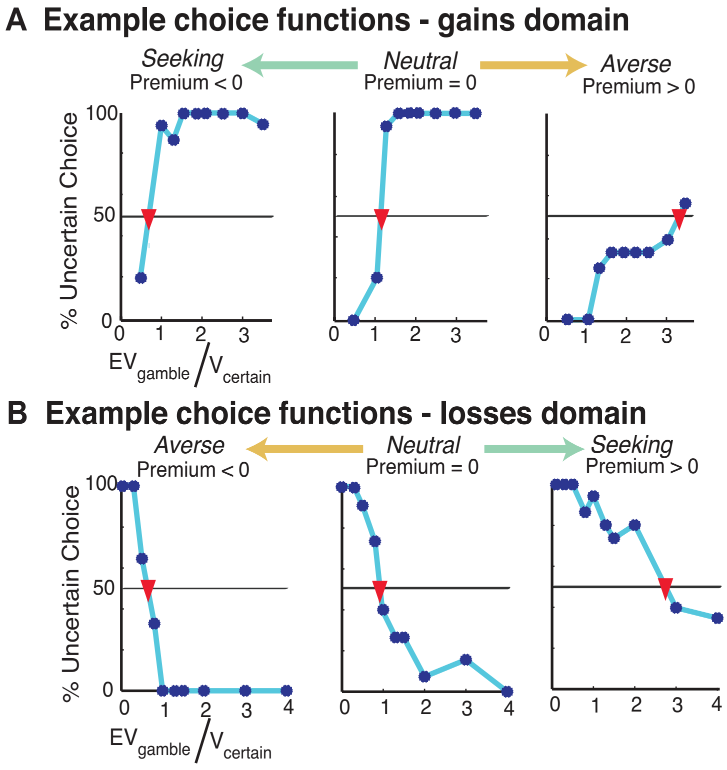

Figure 3.2. Examples choice functions for individual participants. Each subplot shows the choice behavior for 1 participant across the trials where they chose between a risky gamble and a certain monetary option one task. The y-axis indicates the percent at which they selected the gamble option, across 15 trials for each point. The x-axis is the ratio of the expected value of the gamble to the value of the certain option (rEV). (A) In the gains choice task, for 135 risk trials across 9 examined rEV values. (B) In the losses choice task, for 150 risk trials across 10 examined rEV values. Participants' choice functions for the risk trials from each domain-specific task were plotted to show the percent at which they selected the gamble for each examined rEV value. The indifference point of each participant was determined as the projected rEV for where their choice function indicated 50% selection of the gamble (as indicated with an inverted red triangle for these participants). We defined the risk premium value for each participant as their indifference point -1 (to make zero be risk neutral).

The premium value is a measure of the degree to which participant alters the valuation of the absolute expected value of the gamble in relation to outcome uncertainty. As such, a zero premium value reflects no change in valuation (subjective value (SV) = expected value (EV)), a positive value indicates diminished valuation (SV < EV) and a negative value indicates enhanced valuation (SV > EV). This interpretation of valuation applies for both gains and losses premium values. However, in the gains domain, positive/negative premium values indicate risk aversion/seeking, but in the losses domain negative/positive premium values indicate risk aversion/seeking. In both domains, a zero risk premium value indicates risk neutrality.

Our premium metric cannot be derived for participants whose choice functions do not have an indifference point within our sampled range (their choice function does not cross 50% acceptance, see Figure 3.2). We opted to remove such participants from uncertainty preference analyses, as such choice functions are the result of participants not modulating their choice behavior across our large set of relative values of the gamble and certain options (for discussion, see Kurnianingsih et al., 2015). This resulted in the exclusion of: risk gains: 7 RW and 6 TSD; risk losses: 1 RW and 1 TSD; ambiguity gains: 11 RW and 10 TSD; and ambiguity losses: 1 RW and 1 TSD. We note that the exclusion rates across RW and TSD sessions are almost identical.

To facilitate comparison across studies, we note that our risk premium formulation has been previously shown to result in very high correlations with the power function risk preference values, when examined in a large sample ($N \sim 300$, $r > |.6|$ for gains, Stanton et al., 2011) or two moderate samples ($N = 62$, $r > |.7|$ for gains and losses, Kurnianingsih et al., 2015; $N = 72$, $r > |.49|$ for gains, and $r > |.77|$ for losses, Mullette-Gillman et al., 2015). In the current smaller sample, in RW, we find slightly lower correlations for risk preferences in gains ($r(20) = -.41$, $p = .06$) and very high correlations in losses ($r(26) = -.87$, $p < .0001$). For ambiguity preferences, we find uniformly high correlations (gains, $r(16) = -.81$, $p < .001$; losses, $r(26) = -.90$, $p < .0001$), in concurrence with our prior results ($N = 72$, $r > |.77|$ for gains, and $r > |.87|$ for losses, Mullette-Gillman et al., 2015). These consistently high correlations indicate that these two measures of risk preferences are largely capturing the same variance across participants.

Quantifying choice strategy. Choice strategy refers to the relative use of two conflicting information types present in each trial that the participant can rely upon to make their choice – the first is the relative expected value of the two options (rEV), and the second is the probability of winning the gamble (pWIN) (see Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015). While rEV is more likely to lead to higher average rewards, it requires multiple steps to calculate. In contrast, while pWIN information is readily available perceptually, it will lead to lower average rewards. Importantly, across the risk trials of our task, the pWIN and rEV of each trial are fully dissociable (their correlation is zero).

To quantify the choice strategy of each participant, for each domain (gains or losses) we utilized two linear regressions (2 factors × 2 domains) (Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015). Each of these four linear regressions determined the influence of one factor (pWIN or rEV) on the choices of a participant across all risk trials within one domain (gains or losses). The produced R-squared values provide the proportion of choice variance that can be explained by each examined factor (see Figure 3.4A to 3.4D). Therefore, high R-squared values indicate that choices were most likely influenced by that trial information (e.g. a participant that determines their choices solely based on the probability of winning the gamble would have a high R-squared value for the pWIN factor, while a participant whose decision is solely based upon the ratio of the expected value of the gamble to the value of the certain option would have a high R-squared value for the rEV factor), whereas low R-squared values indicate that choices were based on other factors or were made randomly.

We produced the Choice Strategy metric by taking the difference between these R-squared values (rEV minus pWIN) for each domain (see Figure 3.4E to 3.4H). As such, the choice strategy metric directly contrasts utilization of the cognitively demanding calculation of the relative expected values of the certain and the gamble options against utilization of the probability of winning in the gamble option. Choice strategy values are positive when participants utilize rEV information more and negative when they utilize pWIN information more. Participants are considered to be 'maximizing' when they have positive choice strategy (R-squared rEV > R-squared pWIN) and 'satisficing' when they have negative choice strategy (R-squared rEV < R-squared pWIN).

In addition to determination of the choice strategy metric, we also utilized the components of these analyses to examine the question of whether TSD results in an overall decrease in information use. To test this, we calculated a total strategy metric for each participant (for each domain and in each state), as the sum of the R-squared values for the rEV and pWIN regressions. It is important to note that these trial factors are fully orthogonal across trials (i.e., the correlation across trials is zero), so it is mathematically impossible for these factors to account for the same variability in choice behavior in their independent regressions.

We note that as our analytic method only examines the influences of the pWIN and rEV information on the choice behaviors of each participant, as proxies for satisficing and maximizing strategies, we are unable to speak to whether sleep deprivation may have differential effects on the use of other unexamined informational factors. However, we note specifically that one additional factor is very highly correlated with the rEV factor in both tasks – the difference in expected value of the gamble option and the value of the certain option (EVdiff = $EV_g - V_c$), Across trials, this factor has an extremely high inter-trial correlation with the rEV informational factor (gains: $r(133) = .926$, $p < .0001$; losses: $r(148) = .957$, $p < .0001$), and is almost orthogonal to the pWIN factor (gains: $r(133) < .0001$, $p > .99$; losses: $r(148) < .0001$, $p > .99$).

Loss aversion task. We quantified loss aversion, or the relative influence of potential losses to potential gains on choice behavior, utilizing a modified version of the task and analyses of Tom and colleagues (2007). The sole alteration in our version was a reduction in the number of trials to 64 trials (halving the number of sampled increments in each domain). In brief, participants were first endowed with $20 and, on each trial, were given a choice to keep their endowment or risk part of it on an offered gamble. Gambles always had a 50% chance of a gain and a 50% chance of a loss, with gains ranging from $12 to $40 in increments of $4, while losses ranged from -$6 to -$20 in decrements of -$2 (Figure 3.1C). Participants indicated whether they accepted each offered gamble with options of ‘strongly accept’, ‘weakly accept’, ‘weakly reject’ or ‘strongly reject’. No feedback was provided during the task, to prevent learning effects, and participants were informed in the preliminary session that their final payment would be based upon random selection and resolution of one trial from each iteration of the task at the conclusion of the final session.

Quantifying loss aversion. Loss aversion preferences were quantified following the analyses of Tom and colleagues (2007). In brief, a logistic regression was fit to the choices of each participant to determine the differential influence (beta weights) of the potential loss and gain values of the offered gambles on choice behavior (accept or reject). The ratio of these beta weights produced the loss aversion (λ) metric for each participant. Loss aversion values greater than 1 indicate that an individual’s choices were more strongly influenced by the value of the potential losses than the potential gains, while values below 1 indicate the reverse, and values of 1 indicate equal weighting. We collected data from 21 participants. We excluded 4 participants whose behavior in either session indicated unreasonable loss aversion values (such as a lambda of 38). These can be the result of the participant ignoring the value of the possible gain – such as employing a fixed response of accepting all gambles whose loss is below a threshold. Such strategies result in strikingly high loss aversion values, and are not well captured by the theoretical concept of loss aversion. This resulted in a final sample of 17 participants for our loss aversion analyses.

Statistical analyses. All comparisons between TSD and RW conditions are performed utilizing within-subject statistical tests.

Results

Relationship of economic task metrics

As a baseline, we examined the inter-relationships of our economic metrics within the RW state. Risk and ambiguity premiums were highly correlated within each domain (gains: $r(15) = .86$, $p < .0001$; losses: $r(26) = .84$, $p < .0001$). Risk preferences were uncorrelated with choice strategy within either domain (gains: $r(19) = .17$, $p = .46$; losses: $r(26) = -.12$, $p = .53$). These results concur with our prior results using these tasks in young adults (Kurnianingsih et al., 2015).

We found no significant correlation (all $p > .26$, uncorrected) between loss aversion and uncertainty preferences (risk and ambiguity) or choice strategies within either domain. As loss aversion is the ratio of the relative weighting of losses to gains, we examined for potential relationships between loss aversion and the ratio of risk premiums and choice strategies across domains (losses / gains). No significant correlations were found (all $p > .05$, uncorrected), indicating that loss aversion is an independent measure of choice behavior from risk preferences and choice strategy.

In summary, we show very high correlations between risk and ambiguity preferences within a domain, and found no other significant correlations between our decision-making metrics within either domain.

Sleep deprivation reduces vigilant attention

To confirm the robustness of our TSD manipulation, we examined for alterations of PVT response times and attentional lapses, as impaired vigilance is among the most robust effects of sleep deprivation (Lim & Dinges, 2010). PVT data were available for a subset of 18 participants. On average, participants showed slower median reaction times in TSD than in RW (mean ± SD, RW: 242.8 ± 22.3 ms, TSD: 300.9 ± 50.1 ms; $t(13) = 6.41$, $p < .0001$, Cohen's $d = 1.54$). There was also an increase in the number of attentional lapses under TSD (mean ± SD RW: .56 ±.78; TSD: 7.67± 6.74; $t(13) = 4.16$, $p < .0001$, Cohen's $d = 1.52$).

Sleep deprivation does not alter the response times of economic decisions

Given that TSD alters PVT response times, we examined whether TSD also alters response times for economic decisions (Table 1). We found no significant effects of sleep deprivation on response times within either the gains (mean ± SD risk difference: .002 ± .23; $t(28) = .06$, $p = .95$, Cohen's $d = .008$; mean ± SD ambiguity difference: -.02 ± .26; $t(28) = .48$, $p = .63$, Cohen's $d = .07$) or the losses domains (mean ± SD risk difference: -.04 ± .20; $t(28) = .97$, $p = .34$, Cohen's $d = .12$; mean ± SD ambiguity difference: -.03 ± .24; $t(28) = .62$, $p = .54$, Cohen's $d = .10$.). Within both states, participants exhibited faster response times for the gains choice task than the losses choice task (risk RW: $t(28) = 3.52$, $p < .003$, Cohen's $d = .33$; TSD: $t(28) = 2.16$, $p < .039$, Cohen's $d = .38$; ambiguity RW: $t(28) = 2.50$, $p = .02$, Cohen's $d = .46$; TSD: $t(28) = 1.73$, $p = .09$, Cohen's $d = .32$).

Table 3.1. Comparison of economic measures between RW and TSD

	Rested Wakefulness (RW) mean±SD	**Sleep Deprivation (TSD)** mean±SD	***RW vs. TSD*** *p-value****
Gains choice task			
Uncertainty premiums			
Risk (22, 23)*	.48 ± .68	.52 ± .78	.73
Ambiguity (18, 19)	1.52 ± 1.37	1.28 ± 1.46	.76
Risk × Ambiguity	r(15) = .86, p < .0001	r(16) = .43, p = .07	
Strategy			
Choice strategy (29, 29)	-.007 ± .27	-.09 ± .30	**.01**
rEV r^2 (29, 29)	.19 ± .15	.15 ± .14	**.015**
pWIN r^2 (29, 29)	.19 ± .17	.23 ± .19	**.031**
Total strategy (29,29)	.38 ± .14	.38 ± .15	.97
Response time (s)**			
Risk (29, 29)	1.02 ± .31	1.01 ± .34	.95
Ambiguity (29, 29)	1.04 ± .35	1.06 ± .37	.63
Losses choice task			
Uncertainty premiums			
Risk (28, 28)	.01 ± .43	-.03 ± .29	.40
Ambiguity (28, 28)	.01 ± .50	-.10 ± .38	.07
Risk × Ambiguity	r(26) = .84, p < .0001	r(26) = .68, p < .0001	
Strategy			
Choice strategy (29, 29)	.36 ± .15	.34 ± .13	.32
rEV r^2 (29, 29)	.40 ± .12	.38 ± .11	.40
pWIN r^2 (29, 29)	.04 ± .04	.04 ± .05	.42
Total strategy (29,29)	.43 ± .10	.42 ± .12	.57
Response time (s)**			
Risk (29, 29)	1.14 ± .30	1.10 ± .29	.34
Ambiguity (29, 29)	1.19 ± .32	1.16 ± .27	.54
Loss aversion task			
Loss aversion (17, 17)	1.98 ± 1.40	2.16 ± 1.87	.30

* Numbers in parentheses indicate the number of subjects in each group (N RW, N TSD)
**Median response time
***Paired-sample t-tests
Abbreviations: rEV, Relative Expected Value; pWIN, Probability of Winning; s, seconds.

Sleep deprivation does not alter risk or ambiguity preferences

To examine the test-retest reliability of our uncertainty preference metrics, we ran a correlation across sessions. With approximately 1 week between sessions, and no resolution of any gambles until the end of all sessions, we found very strong test-retest reliability between uncertainty preferences for all four uncertainty preference measures (correlations; risk gains: $r(19) = .78$, $p < .0001$; risk losses: $r(26) = .79$, $p < .0001$; ambiguity gains: $r(12) = .55$, $p = .04$; ambiguity losses: $r(26) = .81$, $p < .0001$).

Sleep deprivation did not shift risk preferences within either the gains (mean ± SD difference: .04 ± .47; $t(20) <1$, $p = .73$, Cohen's $d = .06$) or the losses domains (mean ± SD difference: -.04 ± .26; $t(27) <1$, $p = .40$, Cohen's $d = .12$) (see Table 3.1 and Figure 3.3). Risk preferences under both RW and TSD followed the classical pattern (Kahneman & Tversky, 1979), with people being generally risk averse for gains and risk neutral or seeking for losses (mean ± SD, Gains RW: .48 ± .68, TSD: .52 ± .78; Losses RW: .01 ± .43, TSD: -.03 ± .29).

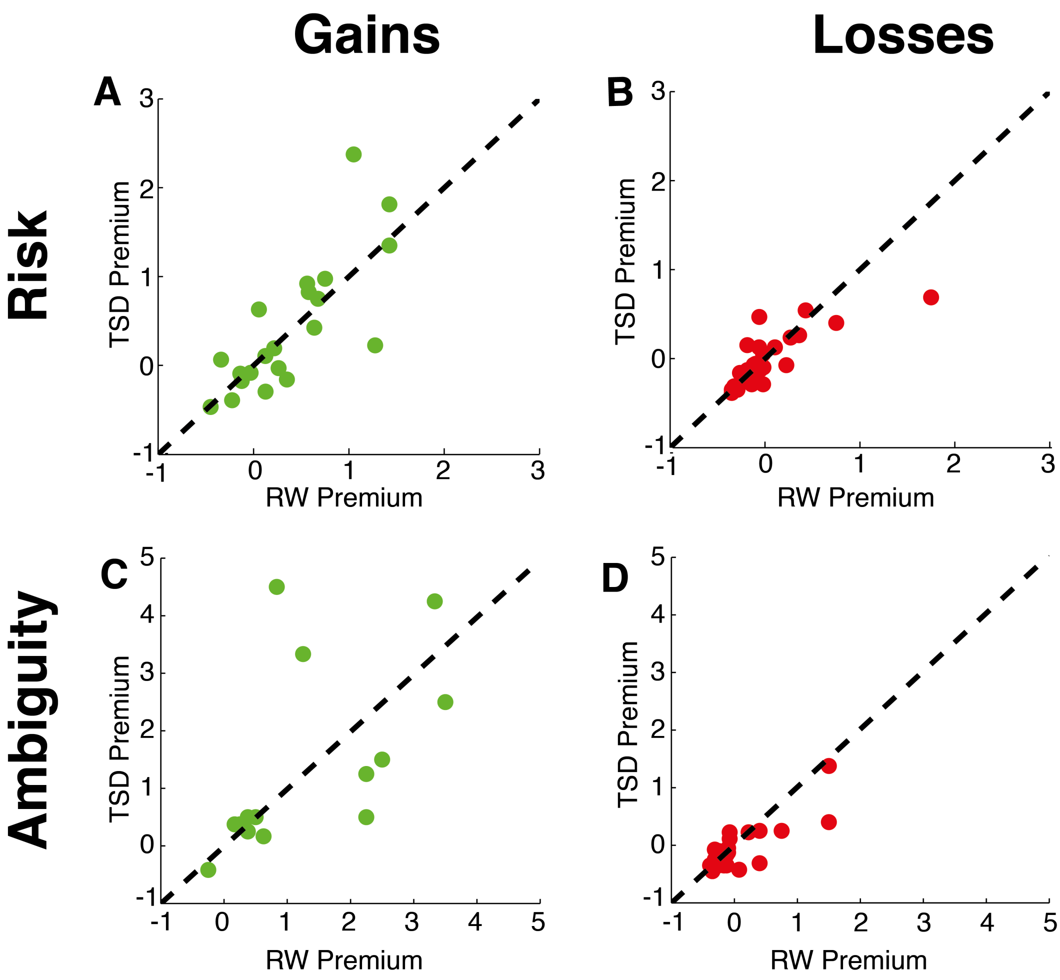

Figure 3.3. Uncertainty preferences. Relationship between subjects' preferences across RW and TSD conditions for (A) Gains risk premium, (B) Losses risk premium, (C) Gains ambiguity premium, and (D) Losses ambiguity premium.

There was also no significant difference in ambiguity preferences between RW and TSD within the gains domain (mean ± SD difference: .12 ± 1.38; $t(13) < 1$, $p = .76$, Cohen's $d = .17$). Within the losses domain, there was a non-significant trend suggesting higher ambiguity seeking during TSD (mean ± SD difference: -.11 ± .29; $t(27) = 1.90$, $p = .061$, Cohen's $d = .24$), with calculation of Cohen's d indicating a small effect size (Cohen, 1988). Overall, participants were significantly more ambiguity averse than risk averse in the gains domain (RW: $t(16) = 4.71$, $p < .0001$, Cohen's $d = 1.03$; TSD: $t(17) = 2.92$, $p = .010$, Cohen's $d = .69$), while no difference between ambiguity and risk preference was found in the losses domain (RW: $t(27) < 1$, $p = .91$, Cohen's $d = .01$; TSD: $t(27) = 1.31$, $p = .20$, Cohen's $d = .21$).

Sleep deprivation does not alter loss aversion preference

We examined the effect of TSD on loss aversion preferences. With ~1 week separation and no resolution of outcomes, loss aversion preferences were highly stationary, with test-retest correlations of $r(15) = .95$, $p < .0001$. Examining for modulation of loss aversion by TSD, we found no significant effect (mean ± SD difference λ : .18 ± .70, $t(16) = 1.06$, $p = .30$, Cohen's $d = .11$).

Choice strategy is highly stationary over sessions

We examined the information that each participant utilized to make their choices through our choice strategy metric. Across sessions, with ~1 week delay and no resolution of outcomes, we found very strong test-retest reliability between choice strategy values within both domains (correlations; gains: $r(27) = .84$, $p < .0001$; losses: $r(27) = .72$, $p < .0001$). This is a strong concurrence in the test-retest reliability of these measures, building upon our previously published 90-minute delay (correlations; gains: $r > .89$; losses: $r > .77$; Mullette-Gillman et al., 2015).

For gains, sleep deprivation decreases use of maximizing information and increases use of satisficing information

Within the gains domain, we found significant modulation of choice strategy by sleep deprivation condition (mean ± SD difference: -.09 ± .16, t(28) = 2.78, p = .010 Cohen's *d* = .31). Concurring with our hypotheses, TSD resulted in decreased choice strategy; that is, diminished use of maximizing information relative to satisficing information (see Figure 3.4 and 3.5). As the choice strategy metric is a composite metric, we examined the effect of TSD on the independent R-squared values for the two component factors – rEV and pWIN. Within the gains domain, TSD resulted in significant alteration of both components – diminished use of the maximizing rEV information (mean ± SD difference: -.04 ± .09, t(28) = 2.58, p = .015, Cohen's *d* = .31) and increased use of the satisficing pWIN information (mean ± SD difference: .05 ± .11, t(28) = 2.27, p = .031, Cohen's *d* = .25).

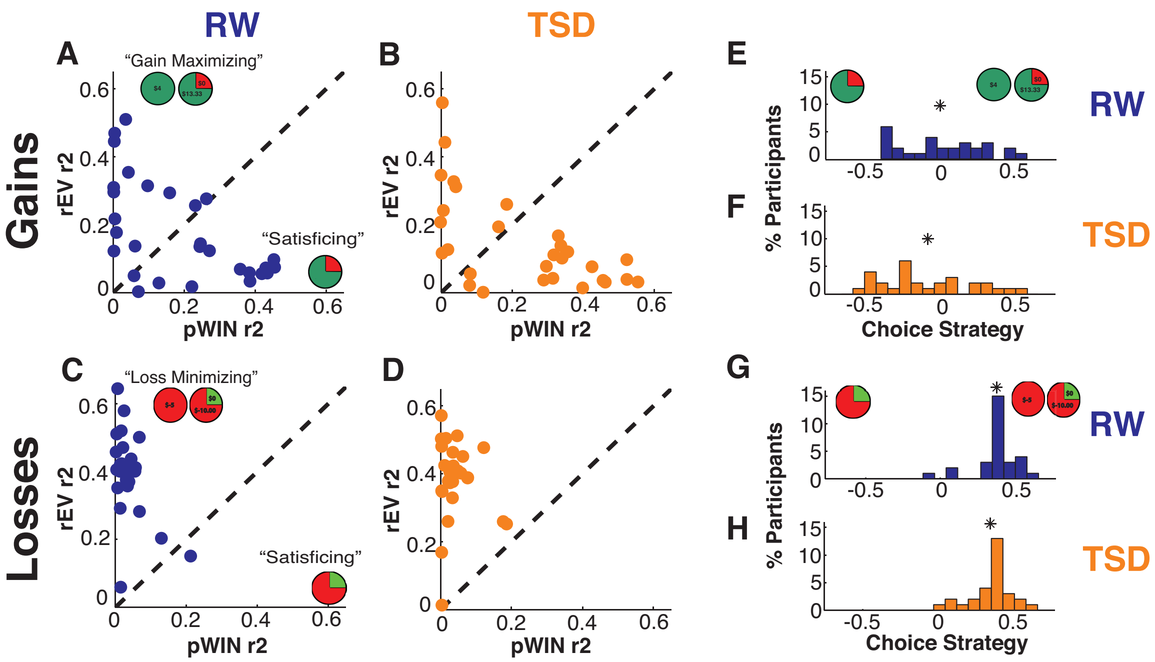

Figure 3.4. Choice strategy metric – utilization of trial information. Relationship between trial variances explained (R-squared) by the rEV and pWIN information for (A) RW gains domain, (B) TSD gains domain, (C) RW losses domain, and (D) TSD losses domain. Distribution of choice strategy values (difference between rEV R-squared minus pWIN R-squared) for (E) RW gains domain, (F) TSD gains domain, (G) RW losses domain, and (H) TSD losses domain. The "*" indicates the mean of each distribution."

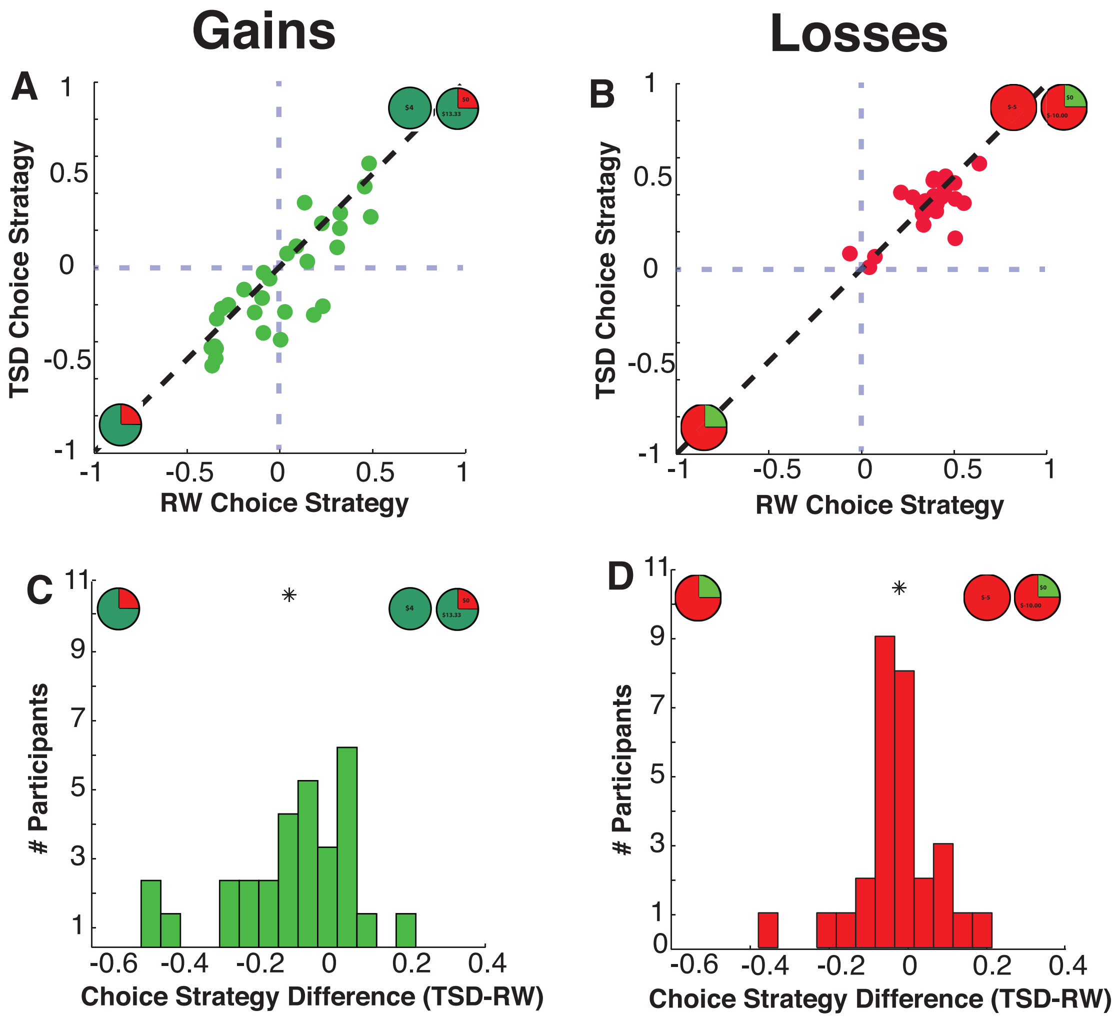

Figure 3.5. Choice strategies. Relationship between subjects' choice strategy across rested wakefulness (RW) and total sleep deprivation (TSD) conditions for (A) Gains choice strategy, and (B) Losses choice strategy. Distribution of differences in choice strategy (TSD minus RW) for the (C) Gains domain and the (D) Losses domain.

Given this clear decrease in strategy in the gains domain, we examined if this change in behavior was related to found reductions in vigilance. Within the 18 participants with vigilance data, we found that individual differences in the effects of TSD on reaction times (PVT RT, TSD-RW) were significantly negatively correlated with the effects of TSD on choice strategy (TSD-RW) in the gains domains ($r(16) = -.47$, $p = .047$) – individuals in which TSD led to longer reaction times in the psychomotor vigilance task also showed reduced choice strategy in the gains choice task.

For losses, sleep deprivation does not alter information use

Within the losses domain, we did not find a significant mean shift in choice strategy between RW and TSD (mean ± SD difference: -.02 ± .10, $t(28) = 1.01$, $p = .32$, Cohen's $d = .14$).

Sleep deprivation does not alter total information use

To test whether TSD resulted in a decrease in the total information that participants used to make their economic choices, we examined our total strategy metric (the sum of the R-squared values of the rEV and pWIN regressions). The total strategy metric showed high within-subject stationarity across states within both domains (gains, $r(27) = .72$, $p < .0001$; losses, $r(27) = .67$, $p < .0001$). Testing for TSD effects, we found no significant differences between RW and TSD within either the gains or losses domains (mean ± SD gains difference: .005 ± .11, $t(28) = .04$, $p = .81$, Cohen's $d = .03$; losses difference: -.01 ± .09, $t(28) = .57$, $p = .57$, Cohen's $d = .09$).

Replicating information use analyses with logistic regressions

The choice patterns of subjects range from linear to logistic across the rEV values (as can be seen in Figure 3.2). Use of linear models could potentially produce misestimations in participants whose choice functions are more logistic (specifically, a participant with a sharp transition will have a lower R-squared value than a matched participant with a gentle slope).

Nonetheless, we chose to use linear models due to a number of competing items: 1) answering our hypotheses required two independent regressions for each participant, to determine the independent contributions (R-squared values) of the pWIN and rEV trial factors; 2) with linear models, the cross-trial correlation of zero between the pWIN and rEV factors prevents omitted-factor bias (i.e., the misestimation of the contribution of a factor due to the absence of the second factor in the regression); and 3) with independent logistic models, omitted-factor bias would be present regardless of the correlation between the included and excluded factors. Although our use of linear models is imperfect, the impact on our principle findings is likely negligible (Hellevik, 2009).

Critically, any such misestimations are independent of the manipulation that is the focus of this manuscript. In each condition (RW or TSD), reduced precision of the degree to which a participant utilized the rEV factor would result in on-average symmetric noise of the point-estimation (reducing overall power), but without a directional bias on the examined manipulation effects (as there is no relationship to the manipulation). We note that the high individual test-retest stationarity we reported previously (section 3.6, with correlations gains $r = .84$ and losses $r = .72$) suggests that the cumulative effects of any such imprecisions are small. In fact (below), we find the exact same pattern of manipulation effects using logistic models as was previously found using linear models.

To test the analytic robustness of our found patterns of change in information use, we replicated our analyses replacing the linear regressions with logistic regressions, and calculating McFadden's pseudo R-squared

(McFadden, 1974). We found very high correlations between the R-squared and pseudo R-squared values from the linear and logistic regressions across the RW and TSD sessions, within both the gains (rEV: $r(56) = .90$, $p < .0001$; pWIN: $r(56) = .90$, $p < .0001$) and losses (rEV: $r(56)$ .73, $p < .0001$; pWIN: $r(56) = .99$, $p < .0001$) domains. We replicated all results contrasting the RW and TSD sessions - a significant decrease in the use of rEV information and an increase in pWIN information in the gains domain only (rEV: gains, $t(28) = 2.95$, $p = .006$, Cohen's $d = .29$; losses, $t(28) = 1.45$, $p = .16$, Cohen's $d = .23$; pWIN: gains, $t(28) = 2.15$, $p = .041$, Cohen's $d = .24$; losses, $t(28) = .46$, $p = .65$, Cohen's $d = .06$), and no alteration of total information used in either domain (the sum of rEV and pWIN pseudo R-squared values; gains, $t(28) = .59$, $p = .56$, Cohen's $d = .09$; losses, $t(28) = 1.36$, $p = .18$, Cohen's $d = .24$).

We note that we could not simply run a multi-factor regression, as it would provide only a single R-squared value (accounting for the joint variance accounted for by both the pWIN and rEV factors) and the estimated coefficients definitionally address a different dimension of behavior (the directional influence of the factor, as opposed to the amount of variance it can explain).

Discussion

We show that sleep deprivation alters economic decision making through alterations of choice strategies. TSD did not significantly alter economic preferences (risk, ambiguity, or loss aversion), decision response times, or the total information used by participants. In contrast, we found that one night of sleep deprivation altered the information that participants relied upon to make their choices, specifically within the gains domain.

In the gains domain, TSD produced a general decrease in choice strategy, which was the result of both decreased use of maximizing information (rEV) and increased use of satisficing information (pWIN). TSD did not alter the total amount that participants utilized these types of information, indicating that in economic decision making TSD produces a switch in what information participants rely upon rather than a decrease in overall information use.

TSD does not alter uncertainty preferences

Our participants exhibited the standard pattern of average uncertainty preferences across the gains and losses domains, during both RW and TSD; that is, participants were, on average, risk averse for gains and risk seeking/neutral for losses (Kahneman & Tversky, 1979). With high test-retest reliability, we found no alterations in uncertainty preferences in either the gains or the losses domains. This represents the first study to explicitly test sleep deprivation effects on uncertainty preferences while controlling for potentially confounding factors such as strategy and learning.

We note that, as compared to our findings, several prior studies have suggested that TSD results in altered uncertainty preferences. This discrepancy may be due to task and metric differences, with previous studies unable to dissociate alterations in uncertainty preferences from related cognitive processes such as reward learning (as in the Iowa Gambling Task, Killgore, 2006). Beyond explicitly testing uncertainty preferences, our task design also allowed us to distinguish alterations of preferences from alterations of strategies. We suggest that this conflict can be resolved through consideration of our observed alterations of choice strategies (see below). That is, prior studies may have ascribed behavioral alterations to preference shifts that may actually have been due to changes in choice strategy.

TSD does not alter loss aversion preferences

We also examined whether TSD results in a change in loss aversion, or the relative weighting of losses and gains. We found no alteration of loss aversion preferences, concurring with the behavioral findings of Venkatraman and colleagues (2011) and their suggestion that behavioral alterations are due to other factors.

TSD decreases choice strategy in the gains domain

Within the gains domain, TSD resulted in a significant decrease in our choice strategy metric. As this is a compound metric, we examined the components and found that TSD both decreased the use of the relative expected value information (rEV) and increased the use of probability information (pWIN). Use of the rEV may be considered a form of 'maximizing strategy' (maximizes expected outcomes, but requires multiple cognitive steps to calculate), while use of pWIN may be considered a 'satisficing strategy' (a simplifying heuristic that utilizes readily-available information at the cost of maximizing rewards). As such, in the gains domain TSD led to decreased use of maximizing strategies and concomitant increased use of satisficing strategies. This result concurs with a recent study by Menz and colleagues (2011), which found a reduction in decision-making quality (higher stochasticity) without a change in preferences.

Further, the individual change (TSD-RW) in choice strategy in the gains domain showed a negative correlation with change in performance on the psychomotor vigilance task. Given the inversion between these scales, with poorer performance corresponding to higher PVT response times and lower choice strategy values, this relationship shows that the individuals who had the most detrimental effect of TSD modulation on PVT also had the greatest reduction in maximizing behavior. This relationship suggests that the mechanisms through which sleep deprivation alters choice strategy in the gains domain is related to the mechanisms for altered response times in the PVT.

Inferring cognitive alterations

Does this pattern of alterations allow us to determine what cognitive processes are affected by sleep deprivation? TSD specifically altered strategy in the gains domain, with decreased use of maximizing information and increased use of satisficing information. Notably, there was a correlation between the degree of change (TSD-RW) in choice strategy and the change in psychomotor vigilance. However, TSD did not alter uncertainty preferences (risk or ambiguity) or loss aversion. These results clearly show the independence of effects in the gains and losses domains, suggesting that the cognitive or neural mechanisms are not simple mirrors. In addition, the domain-specificity of our alteration suggests a possible alternate explanation for the TSD-produced optimism bias found by Venkatraman and colleagues

(2011). In brief, a gains-specific increase in satisficing behavior could have biased behavior in their 5-outcome mixed gamble task (rather than a change in valuation).

Are these results interpretable through a simple two-system model of affect vs. reason? If TSD specifically alters affective processes, such as the subjective valuation of gains or losses, then we may have seen clear changes in risk preferences in either domain. If TSD alters the relative valuation of gains and losses, then we may have seen clear changes in loss aversion. We saw neither of these.

Rather, the effects of TSD were limited to the strategy measures. Based on a dual-system model, this pattern of changed strategy with unaltered preferences could be interpreted to suggest that TSD alters cognitive processes related to reason without altering affect. However in disagreement, we also found no reduction in overall information use, and the changes in strategy were limited to the gains domain.

We caution against interpreting these results based upon such a dual-system approach. Simply, changes in strategy could be the result of changes in reason or motivation. Similarly, changes in risk preferences or loss aversion could not only be produced by altered affect, but could also be derived from changes in reasoning alone.

The clearest indication of the altered cognitive processes responsible for our found alteration in gains strategy come from the strong relationship between the change in strategy and the change in psychomotor vigilance (PVT). This relationship suggests that these effects share an underlying source, but unfortunately our results cannot specify that source.

Conclusions

TSD alters the information participants rely upon to make their decisions, without modulating uncertainty preferences (risk and ambiguity), loss aversion, or decision time. In gains, we identified a decrease in use of maximizing information with a concomitant increase in the use of satisficing information. TSD did not decrease the overall information use.

These results clearly indicate that sleep deprivation negatively impacts decision making in the gains domain, which will lead to lost gains. Such specification of the effects of sleep deprivation on human decision making is critical for the production of effective treatments and policy, including interventions and training for individuals who face unavoidable sleep deprivation (e.g., due to career, medical conditions, or parenting).

Chapter 4: Cognitive fatigue destabilizes economic decision making preferences and strategies[5,6]

The previous two studies examined the differential impact of aging and sleep deprivation on economic decision making across gains and losses domains. The experiment described in this chapter sought to examine the effects of cognitive fatigue. As increase in cognitive fatigue is often related to sleep deprivation (Krueger, 1989) and aging (Avlund, 2010), a priori, we would expect the same effect of all three state modulations on decision making. However, in the previous two chapters, aging and sleep deprivation showed dissociable effects, with aging showing effect in the losses domain only and sleep deprivation showing effect in the gains domain only. By using the same task design across the three different state alterations (aging, sleep deprivation, cognitive fatigue), we were able to contrast their effects on decision making and found clear behavioral dissociation among them and also between the gains and losses domains. Overall, these findings suggests that the three different states influence different neural/cognitive mechanisms and that the gains and losses domains do not share the exact same mechanisms.

Abstract

It is common for individuals to engage in taxing cognitive activity for prolonged periods of time, resulting in cognitive fatigue that has the potential to produce significant effects in behavior and decision making. We sought to

[5] This paper has been previously published: Mullette-Gillman, O.A, Leong, R. L., & Kurnianingsih, Y. A. (2015). Cognitive fatigue destabilizes economic decision making preferences and strategies. *PloS one*, *10*(7), e0132022.
[6] Contributions: OAMG and RLFL conceived and designed the experiments. RLFL performed the experiments. RLFL, YAK and OAMG analyzed the data. OAMG, RFLFL and YAK wrote the paper.

examine whether cognitive fatigue modulates economic decision making. We employed a between-subject manipulation design, inducing fatigue through 60 to 90 minutes of taxing cognitive engagement against a control group that watched relaxing videos for a matched period of time. Both before and after the manipulation, participants engaged in two economic decision making tasks (one for gains and one for losses). The analyses focused on two areas of economic decision making – preferences and choice strategies. Uncertainty preferences (risk and ambiguity) were quantified as premium values, defined as the degree and direction in which participants alter the valuation of the gamble in comparison to the certain option. The strategies that each participant engaged in were quantified through a choice strategy metric, which contrasts the degree to which choice behavior relies upon available satisficing or maximizing information. We separately examined these metrics for alterations within both the gains and losses domains, through the two choice tasks.

The fatigue manipulation resulted in significantly greater levels of reported subjective fatigue, with correspondingly higher levels of reported effort during the cognitively taxing activity. Cognitive fatigue did not alter uncertainty preferences (risk or ambiguity) or informational strategies, in either the gains or losses domains. Rather, cognitive fatigue resulted in greater test-retest variability across most of our economic measures. These results indicate that cognitive fatigue destabilizes economic decision making, resulting in inconsistent preferences and informational strategies that may significantly reduce decision quality.

Introduction

Cognitive fatigue is a ubiquitous human condition, the result of sustained cognitive engagement that taxes our mental resources. The nature of work in our society is changing such that increasingly, work involves demanding cognitive activity, as opposed to physical exertion, with working hours no longer restricted by daylight. Demanding work schedules lead many people to experience cognitive fatigue on a daily basis, and have resulted in high burnout rates (Demerouti et al., 2001; Carod-Artal & Vazquez-Carbera, 2013). Studies examining effects of such fatigue find that persistent mental resource burdens result in diminished motivation, increased distractibility, changes in information processing and poorer mood (Holdings, 1983; Meijman, 2000; Bartlett, 1943; Boksem, Meijman, and Lorist, 2005; Loris, Boksem, & Ridderinkhof, 2005; Sanders, 1998; van der Linden, Frese, & Meijman, 2003; Boksem, Meijman, & Lorist, 2006). Moreover, fatigued participants are more likely to fail to detect errors and less likely to take remedial action, and are more willing to take chances in everyday decision making (Hockey, et al., 2000). Such general deficits can easily lead to diminished performance and health, such as progressive impairment of treatment decisions by doctors (Linder et al., 2014).

We sought to specify the impact of cognitive fatigue on economic decision making, with a focus on uncertainty preferences and strategy. Uncertainty refers to the absence of information about the eventual resolution of probabilistic events, such as in gambles. The two common forms of uncertainty are risk, which involves known probabilities (e.g., a coin flip), and ambiguity, which pertains to probabilities of outcomes that are unknown or cannot be estimated (Knight, 1921; Ellsberg, 1961; Camerer & Weber, 1992). Beyond economic preferences, we also examined what information the participant utilized to inform their choice (Kurnianingsih et al., 2015). We contrasted between two dominant types of information presented in each trial, corresponding to maximizing and satisficing strategies. Maximizing features calculation of the relative expected value of the two options, the determination of which requires multiple mathematical calculations. Satisficing focuses on the probability of winning, which is simply visually observed as the proportion of a circle segment. These strategies differ in terms of cognitive cost, with satisficing less cognitively taxing than maximizing.

A priori, we hypothesized that cognitive fatigue would result in increased satisficing strategies, as fatigued participants opt for less effortful strategies over those requiring more mental resources. This was based on two directions of prior findings. First, studies suggest that cognitive fatigue results in compromised top-down control mechanisms with relative sparing of automatic processes (van der Linden & Eling, 2006). Secondly, aversion to further effort is a common feature of mental fatigue (Boksem, Meijman, & Lorist, 2006; Lorist et al., 2000; van der Linden, Frese, & Meijman, 2003; Robert & Hockey, 1997). Fatigued individuals may seek to minimize the energetic costs by opting for strategies that require lower levels of effort (Boksem & Tops, 2008).

We investigated the impact of cognitive fatigue on economic decision making, specifically alterations of uncertainty preferences and/or choice strategies. We employed two incentive-compatible economic decision making tasks, examining for alterations in economic decision making independently across both the gains and the losses domains. We utilized a between-subjects design, comparing participants that engaged in a cognitively taxing task (fatigue group) and those that watched relaxing videos for an equivalent period of time (control group). We found that cognitive fatigue did not produce a reliable shift in individual uncertainty preferences or choice strategies, contrary to our initial hypotheses. Rather, cognitive fatigue resulted in significantly greater test-retest variability across multiple measures. These results indicate that cognitive fatigue results in the destabilization of economic decision making, highlighting the dangers of fatigue.

Materials and Methods

Participants

All participants provided written informed consent under a protocol approved by the National University of Singapore Institutional Review Board (IRB). Our sample consisted of 76 university students (41 males) with an age range of 19-26 years (M = 22.3 years, SD = 1.74), recruited through advertisements at the National University of Singapore. Data were collected in 2 samples. In the initial sample, 44 participants took part in the study and were randomly assigned to a fatigue (N = 19) or control (N = 25) conditions. Examining the fatigue manipulation for these participants indicated that although the fatigue condition reported cognitive fatigue and significantly higher levels of cognitive effort expended, there was no decline in performance in the N-back task used as the manipulation task. While this effect has been previously reported, we opted to enhance the cognitive fatigue manipulation to ensure that our manipulation was sufficient (Shighara et al., 2013). The second sample of data collection was an additional 32 participants in an extended fatigue condition, with the intention of merging the two samples of fatigue groups if they were not statistically different.

Four participants were excluded from analyses within the fatigue group, as they did not report successful inducement of cognitive fatigue following the manipulation task. Our final sample was 25 participants (11 males; $M = 21.9$ years, $SD = 1.44$) in the control condition and 47 participants (28 males; $M = 22.5$ years, $SD = 1.87$) in the fatigue condition. All participants were asked to abstain from alcohol and caffeine 24 hours before the experiment.

Study procedure

Each experimental session lasted approximately 2.5 hours, for which participants were paid \$10 plus an additional \$0 to 10 (dependent on the resolution of one randomly selected trial for each choice task). Following IRB consent, each session proceeded in the following order: 1) initial questionnaires, 2) pre-manipulation phase, 3) manipulation phase, 4) post-manipulation phase (see Figure 4.1A). At the beginning of the session, participants were briefed on the procedure and asked to perform at their best.

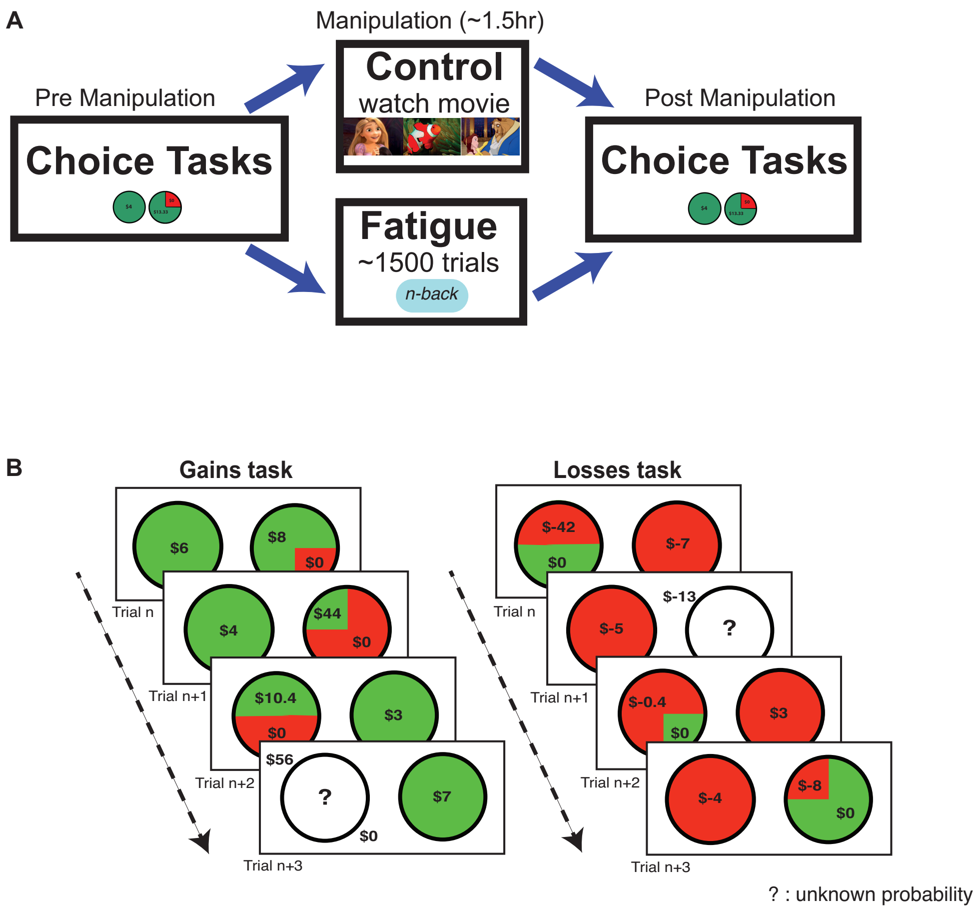

Figure 4.1. Experimental procedures and tasks. (A) All participants filled in the initial questionnaires, followed by a pre-manipulation risk task. In the manipulation period, participants in the fatigue condition performed 5-7 blocks of 300 trials of the N-back task to induce fatigue. Participants in the control condition spent an equivalent amount of time (approx. 90 min) watching relaxing videos. After the manipulation phase, all participants performed the risk task again. (B) The economic decision making task comprised of gains and losses domains, whereby participants were required to choose between a certain or gamble option. They were given no time limit to respond. Participants were paid based on random selection and resolution of one trial from each domain after the completion of the entire experiment.

Initial questionnaires. Participants filled in questionnaires on their demographics, their recent health status, a self-reported cognitive fatigue question, and the Rating Scale Mental Effort (RSME) to assess cognitive fatigue (subjective fatigue measures; see section below).

Pre-manipulation phase. Next, all participants completed the two computerized economic decision making tasks. Participants were informed that one trial of each task would be randomly selected and resolved at the end of the whole experiment to determine their total payment. Importantly, no gambles were resolved until the completion of the experiment to prevent behavioral alterations due to outcome feedback (i.e., learning effects).

Manipulation phase. The manipulation phase followed, with differential treatments for the participants in the fatigue and control conditions. Participants in the fatigue condition performed a cognitively demanding N-back task (5-7 blocks of 300 trials, 2-back) for approximately 90 minutes, while participants in the control group spent 90 minutes watching relaxing videos of nature and animated cartoons. Participants in the non-fatigue group were told to relax and enjoy the videos. The aim was to keep them sufficiently engaged such that they would not be drowsy, but rather, in a neutral state of wakefulness. They were provided with a menu of 3 videos that they could freely switch between: 1) BBC's 'The Life of Birds', 2) Disney's 'Beauty and the Beast', 3) Disney's 'Tangled'. All participants were limited to water (no food or other drinks) for the duration of the study.

Post-manipulation phase. Participants completed the self-reported cognitive fatigue question and RSME scale. Participants then repeated the two computerized economic decision making tasks. Participants were reminded that one trial from each task would be randomly selected and resolved at the end of the experiment to determine their final compensation.

At the end of the session, one trial from each of the 4 economic tasks was randomly selected and resolved. Participants were presented with their earnings and provided the opportunity to ask any questions they might have about the experiment.

Experimental design

Subjective fatigue measures

Throughout the experiment, participants filled in two short questionnaires probing state subjective fatigue and effort (below) (see Figure 4.2). The initial questionnaires were filled in with the initial demographic questionnaires, the second after the pre-manipulation economic task, the third to seventh (or ninth) were filled in after each block of the N-back task, and the last questionnaire was filled in after the post-manipulation economic tasks.

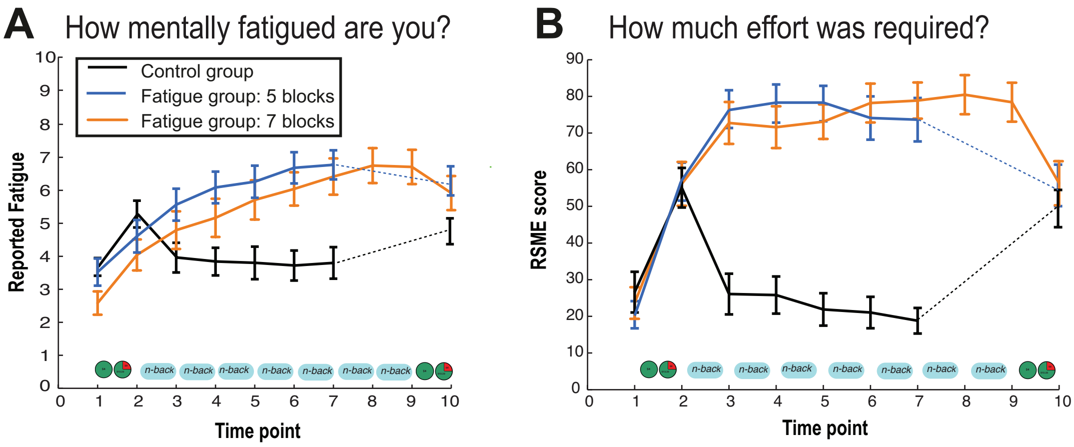

Figure 4.2. Cognitive fatigue ratings. State fatigue and effort across the experimental protocol. The fatigue (orange bars) and control groups (light and dark blue bars: 5-blocks and 7-blocks of N-back respectively) did not differ significantly in (A) self-reported cognitive fatigue pre- manipulation and (B) RSME scores, at baseline. However, post- manipulation, the fatigue group reported significantly higher cognitive fatigue and RSME scores as compared to the non-fatigue group, suggesting that the manipulation was successful in inducing fatigue in the fatigue groups.

RSME. The Rating Scale of Mental Effort (RSME) measures the subjective amount of effort participants have engaged in (Zijlstra, 1993). It is a state measure consisting of one question, asking the respondent how much effort he or she had to invest to perform the activities just completed. This scale is scored from 0 to 150, with verbal anchors of ‘absolutely no effort’ to ‘extreme effort’, respectively. The RSME has been used in numerous studies investigating cognitive fatigue, with significant increases in reported cognitive effort invested interpreted as indicating cognitive fatigue (van der Linden & Eling, 2006).

Self-reported fatigue. Direct self-reported fatigue was assessed with the question of “How cognitively fatigued are you?” with responses on a 10-point scale ranging from 1-not at all to 10-extremely fatigued.

Cognitive fatigue manipulation: N-back task

Cognitive fatigue was induced in participants through completion of 1500 or 2100 trials of the N-back task (5-7 blocks of 300 trials), over approximately 60 to 90 minutes (depending on number of blocks). The N-back task is often associated with studies of working memory, and has been shown to tax working memory (Shighara et al, 2013; Bailey, Channon & Beaumont, 2007; Baddeley, 2003; Jaeggi et al., 2008). On each trial, participants were required to respond with a right button press for the target stimulus and a left button press for any non-target stimulus. We utilized a 2-back condition, in which targets were defined as the letter that is the same as the letter that was presented two trials prior to the current trial. Stimuli were letters of the alphabet, and the full range of letters was used. Each trial was 2 seconds (consisting of 500 ms presentation of white letters in the middle of a black screen and 1.5 seconds for response and feedback), with an inter-trial interval of 200 ms. These values resulted in approximately 15 minutes for each block, with approximately 12 minutes of active task (plus additional time to fill out the pen-and-paper effort and fatigue questionnaires, and restart the task). The task was performed on a computer using MATLAB (v7.10.0, Mathworks, Inc.) and Psychtoolbox extensions (v3) (Brainard, 1997; Pelli, 1997; Kleiner et al., 2007).

Economic decision making tasks

We employed two computerized economic decision making tasks, the first relating to the domain of gains (gains choice task), and the second relating to the domain of losses (losses choice task) (Kurnianingsih et al., 2015; Stanton et al., 2011). On each trial, participants chose between a certain option and one of the uncertain options (risky or ambiguous).

The gains choice task consisted of 135 risky trials and 30 ambiguous trials intermixed with each other. The amount of money offered by the certain option for both risky and ambiguous trials ranged from $3 to $7. In the risky trials, participants were offered a gamble of known probability with three possible probabilities of winning (25%, 50% and 75%) and nine relative expected values (ratio of expected value of the gamble over the value of the certain option; 0.5, 1.0, 1.3, 1.6, 1.9, 2.2, 2.5, 3.0 and 3.5). These resulted in potential winnings from $2 to $98. In the ambiguous trials, participants were offered a gamble with an undetermined probability, having been told that we would randomly select a probability (from 0 to 1) before randomly resolving the gamble. For ambiguity trials, we examined six ratios of expected value (0.5, 1.0, 2.0, 3.0, 4.0 and 6.0), calculated using a 50% probability based on the law of large numbers. These resulted in potential winnings from \$2 to \$168.

The losses choice task mirrored the gains choice task save for alteration of the sign of the value of the options (certain options are certain losses, and gambles feature a potential loss against a potential zero outcome), and adjustment of the EV_G/V_C to provide a greater density of rEV values below 1. Ten relative expected values were examined for both risky and ambiguous trials (0.1, 0.3, 0.5, 0.8, 1.0, 1.3, 1.5, 2.0, 3.0 and 4.0). These resulted in 150 risky trials and 50 ambiguous trials, with potential losses ranging from \$0.40 to \$112 for risk trials and ambiguous trials. Figure 4.1B illustrates trials encountered by participants in both the gains and losses domains.

Prior to beginning either task, participants were reminded that their final monetary compensation would include a proportion of the total monies they gather from resolving a randomly selected trial from each task (four altogether; two tasks in the pre-manipulation phase and two tasks in the post-manipulation phase). Both tasks were self-paced for all trials.

Uncertainty preference metrics

Across both the gains choice task and the losses choice task, we were interested in examining the effects of cognitive fatigue on four different uncertainty preferences – risk in gains, ambiguity in gains, risk in losses, and ambiguity in losses. With the performance of each task both before and after the manipulation, this resulted in a total of 8 preference values for each participant.

Each preference value was determined through psychometric determination of the degree to which participants altered the value of that type of gamble, relative to the certain option (Stanton et al., 2011). To derive this metric, choice functions were constructed by plotting the percentage of choices of the uncertain option as a function of the ratio of the expected value of the gamble to the value of the certain option (EV_G/V_C) (see Figure 4.3 for example choice functions). An indifference point was determined as the first point at which the choice function crossed 50%, indicating the ratio at which the participant was indifferent between the gamble and certain options. This indifference point was modified by subtracting 1 to produce a premium metric – a measure of how participants alter the expected value of a gamble option due to the probabilistic outcome being unknown. Within both domains, a premium value of 0 indicates neutrality. Within the gains domain, a positive premium indicates aversion (devaluing the gamble) and a negative premium value indicates seeking (increasing the value of the gamble). The relationships are inverted in the losses domain, resulting in positive premium values indicating seeking and a negative premium value indicating aversion.

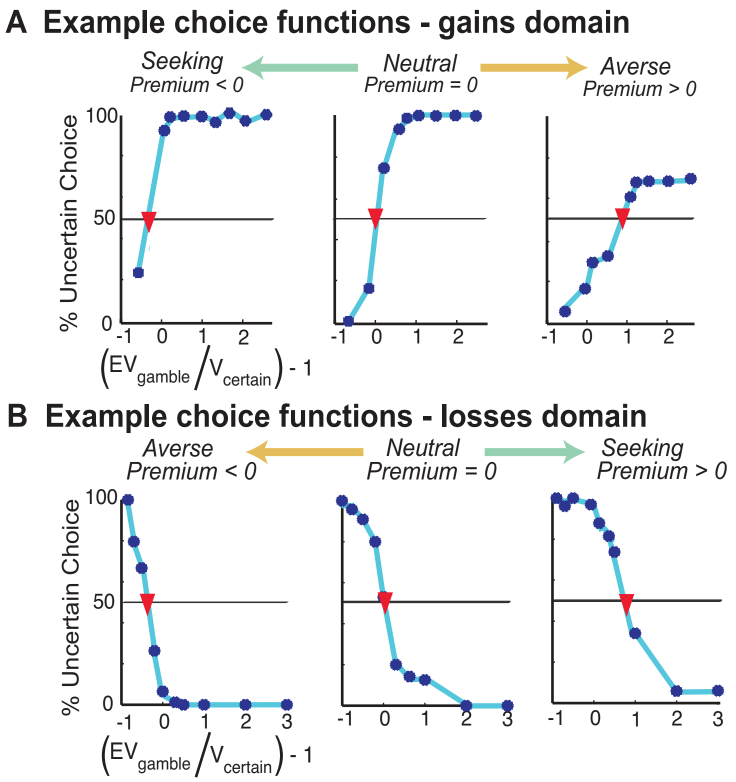

Figure 4.3. Example choice functions. (A) In the gains domain, the range of risk preferences is represented on a continuum from risk seeing (left) to risk averse (right). The indifference point of each choice function is marked with a red inverted-triangle. Risk premium is determined by the value on the ‘(rEV_G / V_c) -1’ (x-axis) at this indifferent point. (B) In the losses domain, the range of risk preferences is represented on a continuum from risk averse (left) to risk seeking (right).

Of note, a small number of participants presented choice functions that did not cross the 50% mark. We are unable to calculate the preference values for such choice functions. Furthermore, we cannot differentiate between whether these participants were engaging their preferences or simply relying on satisficing heuristics (such as always choosing the certain option) (for further discussion, see Stanton et al., 2011 and Kurnianingsih et al., 2015). As such, these participants were excluded from specific analyses, resulting in differential subject counts across tests. Final counts for each metric for each domain are shown in Table 4.1.

Table 4.1. Mean (standard deviation) differences in uncertainty premiums and information strategy metrics in the gains and losses domains between controls and fatigued subjects

	Control		**Fatigue**		
	Means (*SD*)	N	Means (*SD*)	N	*p*
Gains Uncertainty Premium					
Risk	-.121 (.213)	14	-.248 (.721)	30	.524
Ambiguity	-.213 (.739)	13	-.417 (1.283)	27	.599
Information strategy					
Choice strategy	-.096 (.186)	23	-.096 (.205)	43	.995
rEV r^2	-.031 (.108)	23	-.064 (.087)	46	.186
pWIN r^2	.065 (.122)	23	-.028 (.143)	43	.299
Losses Uncertainty Premium					
Risk	.035 (.400)	23	-.090 (.582)	43	.364
Ambiguity	-.016 (.299)	23	-.006 (.545)	41	.937
Information strategy					
Choice strategy	-.005 (.135)	25	-.026 (.150)	45	.576
rEV r^2	-.002 (.104)	25	-.015 (.122)	45	.647
pWIN r^2	.003 (.049)	25	.010 (.047)	45	.555

Mean differences are calculated as post-pre.

In order to facilitate generalization and comparison of these results, we additionally calculated our participants' pre-manipulation uncertainty preference using a power function metric, and tested the correlation of this metric with our premium metric. Previously, we have found very high correlations in these metrics across two samples of younger adults (N~300, r > |.7|; N=62, r > |.7|) (Stanton et al., 2011; Kurnianingsih et al., 2015). In the current sample, we found high correlations within both domains for both risk (Gains: $r(48) = -.497, p < .001$; Losses: $r(66) = -.640, p < .0001$) and ambiguity (Gains: $r(38) = -.773, p < .0001$; Losses: $r(62) = -.877, p < .0001$) preferences. These high correlations indicate clearly that these varying specific formulations of risk preferences are able to largely capture the same variance across participants.

Choice strategy metric

We investigated the informational strategies that participants employed in making their decisions during the gains choice and losses choice tasks. Specifically, we were interested in contrasting the reliance on two dominant competing strategies, with one corresponding to maximizing behavior and the other to satisficing. The maximizing strategy is to compute the ratio of the expected value of the gamble to the value of the certain option (rEV). The satisficing strategy is to simply rely upon the probability of winning the gamble (pWIN), which is evident in the proportion of the pie-shaped representation. Employing the maximizing strategy (rEV information) is more cognitively taxing as it requires mathematical calculations, but it is the optimal strategy, as on average it will result in higher outcomes. The use of the satisficing strategy (pWIN information) is much less effortful as it recruits readily available perceptual information (probability is inferred from coloured segments of the pie), but results in lower expected outcomes on average.

To compare the relative influence of these strategies for each participant, we determined how much of the variance in their choices (across trials) could be accounted for by each factor. This was done through independent linear regressions, which determines how much influence the variation in the examined factor across trials has on the choices made on those trials (in the R-squared value). Importantly, in this task, the value of the pWIN and rEV for each trial are orthogonal across trials (correlation is zero), so the independent regressions cannot result in these factors accounting for the same choice variance.

To compare how much each participant relied upon each of these competing strategies, we contrasted them directly by taking the difference in their R-squared values (rEV minus pWIN) to produce our 'choice strategy' metric. If choice strategy is positive, this indicates that a participant is maximizing (relying more on rEV information than pWIN information). If choice strategy is negative, the participant is satisficing (greater use of pWIN information over rEV information). A value of 0 would indicate that a participant is using the two types of information equally.

Statistical analyses

All statistical analyses were performed with SPSS version 20 (IBM, US) and MATLAB (v7.10.0, Mathworks, Inc.). All statistical tests were two-tailed and the significance level was set at $p < 0.05$.

To compare the effects of our manipulation on the fatigue and control groups, we calculated a difference metric for each of our preference and choice strategy measures, taking the post minus pre scores.

Results

Fatigue samples were not statistically different

We collected two fatigue groups of participants for this experiment, varying the degree of the fatigue manipulation. The initial sample ($N = 19$) performed 5 blocks of 300 trials of the N-back task (~60 minutes), while the later sample ($N = 32$) performed 7 blocks of 300 trials of the N-back task (~90 minutes).

Comparing the initial and later sample, we found no significant differences in pre- or post- RSME manipulation scores or self-reported cognitive fatigue between the 5 blocks or 7 blocks manipulation groups ($p_{RSME\ pre} = .705$; $p_{RSME\ post} = .391$; $p_{fatigue\ pre} = .080$; $p_{fatigue\ post} = .667$). As participants did not self-report differences in fatigue or effort, we merged the two groups into a single fatigue group ($N = 47$) for all subsequent analyses.

Performance on N-back task

Participants in the fatigue condition completed 5 or 7 blocks of 300 trials of the N-back task (Table 4.2). To examine whether performance declined over blocks, we compared block 4 (peak performance) and the final block (block 5 or 7) on measures of percentage of correct trials, misses and false alarms. Paired t-tests revealed no significant difference for misses and false alarms between block 4 and the final block (misses: $t(48) = -.382$, $p = .704$); false alarms: $t(47) = -1.263$, $p = .213$), and a trend toward significance for percentage of correct trials ($t(48) = 1.840$, $p = .072$). Overall, performance was maintained across trials.

Table 4.2. Mean (standard deviation) performance on N-back task from block 1 to 7.

	Block 1	**Block 2**	**Block 3**	**Block 4**	**Block 5**	**Block 6**	**Block 7**
N	51	51	51	51	49	25	25
Correct (%)	73.12 (16.07)	83.73 (14.34)	85.07 (13.20)	85.46 (13.84)	84.79 (14.63)	85.65 (11.88)	86.81 (12.65)
Misses (%)	10.31 (5.46)	7.14 (5.69)	6.58 (5.08)	7.28 (6.35)	7.02 (5.83)	8.23 (7.11)	7.37 (7.37)
False alarms (%)	7.66 (5.07)	5.39 (3.81)	5.58 (4.25)	4.97 (5.25)	5.78 (5.87)	5.07 (4.76)	5.29 (5.02)
Response time (s)	.74 (.30)	.68 (.31)	.63 (.25)	.61 (.24)	.60 (.25)	.58 (.14)	.58 (.13)

Response times are the mean of individual medians, in seconds.

Cognitive fatigue manipulation check: higher effort and fatigue

Pre-manipulation, the fatigue and control groups presented similar baseline levels, with no significant differences in their RSME scores or self-reported cognitive fatigue levels (RSME, fatigue group, $M = 22.3$, $SD = 18.5$; control group, $M = 26.6$, $SD = 27.2$; $t(69) = .783$, $p = .436$) (Figure 4.2B) (self-reported fatigue, fatigue group: $M = 3.00$, $SD = 1.85$; control group: $M = 3.68$, $SD = 1.31$; $t(69) = 1.626$, $p = .108$) (Figure 4.2A).

To ensure the cognitive fatigue manipulation was overall effective, we examined the change in RSME scores and self-reported cognitive fatigue levels across groups. Change values were calculated as the differences between the last values prior to the second economic task minus their initial reported values. Significant differences were found across our two subject groups, with significantly higher levels of effort and resultant cognitive fatigue in the manipulation group (RSME, $t(65) = 8.78$, $p < .0001$; cognitive fatigue, $t(69) = 7.57$, $p < .0001$).

To examine whether there were differences between fatigue and control groups RSME scores we ran two repeated measures ANOVAs with Greenhouse-Geisser correction comparing across the 6 time points where effort and fatigue levels were measured (initial and each subsequent ~15 minutes, between blocks for the fatigue group). For the first, examining RSME scores (self-reported effort), we found significant differences across time points between the fatigue and control groups ($F(2.85, 182.32) = 44.38$, $p < .0001$). Post-hoc t-tests with full-Bonferroni correction to account for the 6 between-group comparisons (adjusted threshold $p = .008$) revealed no difference at the initial time point between fatigue and control groups (pre-manipulation, $t(67) = -.162$, $p = .872$), but significant differences for all subsequent time points ($t > 7.50$, $p < .0001$).

For the second, examining self-reported cognitive fatigue levels, we also found significant differences across time points for fatigue levels between the fatigue and control groups ($F(2.36, 162.78) = 37.89$, $p < .0001$). The pattern was very similar to that found prior, with no significant difference between groups at the initial or second time point (full-Bonferroni adjusted threshold $p = .008$; initial, $t(69) = 1.95$, second, $p = .056$; $t(69) = 1.90$, $p = .062$), and significant differences between groups for all subsequent time points ($t > 2.89$, $p < .006$).

Overall, these results demonstrate that prolonged performance on the N-back task successfully induced a state of cognitive fatigue, in accordance with previous reports (Shighara et al., 2013; Massar et al., 2010).

Relationship between subjective and objective fatigue

Within the fatigue group, we examined whether there were relationships between the change in self-reported levels of fatigue (and effort) and performance on the N-back task (correct %, miss %, false alarm %, and response time) – examining if there are relationships between objective and subjective fatigue. For each of these measures, we calculated the change measure by subtracting the value in block 1 from the value in block 5. We used a full-Bonferroni correction to account for the 4 correlations performed on each of the subjective measures of fatigue (change in fatigue and change in effort), resulting in a threshold of $p = .0125$. None of the relationships were found to be significant.

Cognitive fatigue does not shift economic decision making

To examine the effects of cognitive fatigue on our economic decision making metrics (preferences and choice strategies), we compared the mean difference in changes in economic measures (post-pre) between the fatigue and control group (Tables 4.1 and 4.3).

Table 4.3. Pre- and post- manipulation means (standard deviations) in uncertainty premiums and information strategy metrics in the gains and losses domains for both controls and fatigued subjects.

	Control				Fatigue			
	Pre	N	Post	N	Pre	N	Post	N
Gains Uncertainty Premium								
Risk	.554 (.607)	15	.518 (.587)	16	.810 (.853)	35	.422 (.797)	31
Ambiguity	1.392 (1.884)	15	1.007 (1.003)	14	1.530 (1.250)	28	1.013 (1.244)	29
Information strategy								
Choice strategy	.042 (.330)	24	-.048 (.391)	24	.064 (.270)	46	-.0495 (.243)	44
rEV r^2	.221 (.169)	24	-.194 (.176)	24	.250 (.145)	46	-.050 (.243)	44
pWIN r^2	.180 (.184)	24	.241 (.234)	24	.142 (.155)	46	.175 (.164)	44
Response time (s)	1.665 (.623)	25	1.187 (.418)	25	1.564 (.606)	47	.1075 (.399)	47
Losses Uncertainty Premium								
Risk	.192 (.419)	23	.236 (.579)	24	.120 (.498)	45	.039 (.487)	43
Ambiguity	.040 (.337)	23	.024 (.353)	23	.010 (.385)	42	-.004 (.573)	42
Information strategy								
Choice strategy	.387 (.210)	25	.382 (.187)	25	.359 (.128)	46	.330 (.147)	45
rEV r^2	.435 (.139)	25	.433 (.129)	25	.380 (.120)	47	.369 (.122)	45
pWIN r^2	.047 (.082)	25	1.356 (.367)	25	.1723 (.569)	47	1.176 (.396)	46
Response time (s)	1.878 (.600)	25	1.356 (.368)	25	1.723 (.569)	47	1.176 (.401)	46

Response times are the mean of individual medians.

Cognitive fatigue does not shift response times

Cognitive fatigue did not alter response times in either the gains or losses domains. We found no significant main effect of fatigue on response time within either the gains choice task (t-test, Control: M_{diff} = -0.48, SD_{diff} = .48; Fatigue: M_{diff} = -.49, SD_{diff} = .41; $t(70) = .110$, $p = .913$) or the losses choice task (Control: M_{diff} = -.52, SD_{diff} = 0.40; Fatigue: M_{diff} = -.53, SD_{diff} = .40; $t(69) = .112$, p = .911) (Tables 4.1 and 4.3).

Cognitive fatigue does not shift risk or ambiguity preferences

For each metric, we calculated the change in preference or strategy (post-pre) and compared between the fatigue and control groups with a simple independent sample t-test (Table 4.1). We excluded one participant as an outlier in the gains domain analyses, as their risk difference value (risk premium_{post} – risk premium_{pre}) was > 5*SD* from the mean ($M = .198$, SD = .363) (Tables 4.1 and 4.3).

Within the gains domain, we found no significant main effect of fatigue on risk premium (Control: M_{diff} = -0.12, SD_{diff} = .21; Fatigue: M_{diff} = -.12, SD_{diff} = .21; $t(42) = .642$, $p = .542$) or ambiguity premium (Control: M_{diff} = -.21, SD_{diff} = .74; Fatigue: M_{diff} = -.42, SD_{diff} = 1.28; $t(38) = .531$, $p = .599$) (Table 4.1 and Figure 4.4).

Within the losses domain, similarly, we found no significant main effect of fatigue on risk premium (Control: M_{diff} = .04, SD_{diff} = .40; Fatigue: M_{diff} = -.90, SD_{diff} = .58; $t(64) = .915$, $p = .364$) or ambiguity premium (Control: M_{diff} = -.02, SD_{diff} = .30; Fatigue: M_{diff} = -.01, SD_{diff} = .55; $t(62)$ = .080, $p = .937$) (Table 4.1 and Figure 4.4).

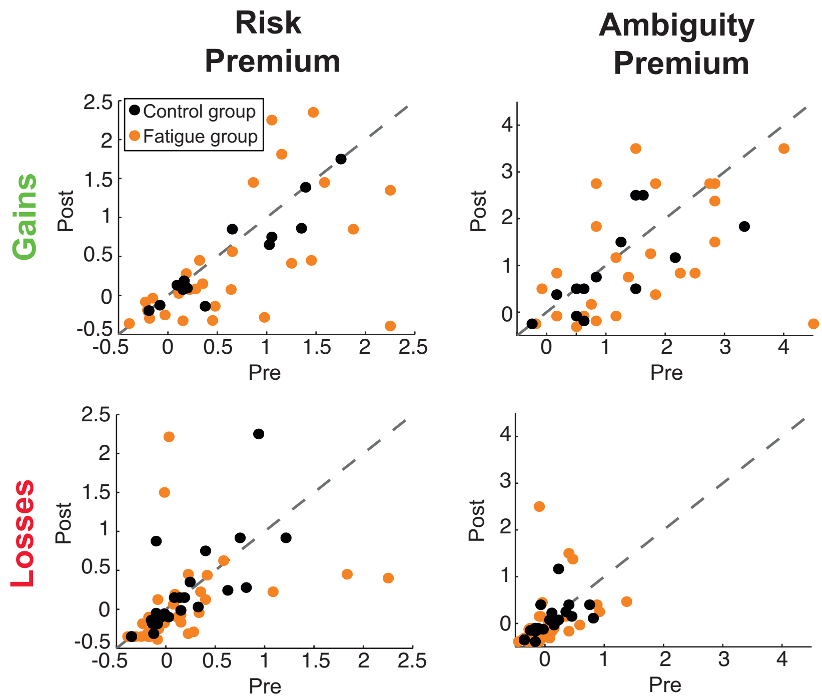

Figure 4.4. Uncertainty preferences in the gains and losses domains. Relationship between pre- and post- manipulation risk and ambiguity premiums values for fatigue (blue) and control (orange) groups in the gains and losses domains.

Cognitive fatigue does not shift choice strategy

Analyses of choice strategy metrics revealed a similar pattern as with the preference metrics. Within the gains domain, there were no significant differences in the change in choice strategy between the fatigue and control groups (Control: M_{diff} = -.10, SD_{diff} = .19; Fatigue: $\mathrm{M}_{\mathrm{diff}}$ = -.10, SD_{diff} = .21; $t(64) = .006$, $p = .995$) (Table 4.1 and Figure 4.4).

As the choice strategy metric is a composite, and a lack of difference in the composite measure does not mean there is no change in the components, we also examined whether there were any significant differences in the use of rEV and pWIN information separately. Concurring with the composite measures, we found no significant effect of cognitive fatigue on either component (rEV r^2 [Control: M_{diff} = -.03, SD_{diff} = .11; Fatigue: M_{diff} = -.06, SD_{diff} = .09; $t(67) = 1.338$, $p = .186$] and pWIN r^2 [Control: M_{diff} = .07, SD_{diff} = .12; Fatigue: M_{diff} = 9.03, SD_{diff} = .14; $t(64) = 1.048$, $p = .299$]).

The same pattern of results were found in the losses domain (Table 4.1 and Figure 4.4), with no significant difference in the change in choice strategy between the two groups (Control: M_{diff} = -.01, SD_{diff} = .14; Fatigue: M_{diff} = -.03, SD_{diff} = .15; $t(68) = .562$, $p = .576$) and no alterations of the independent components (rEV r^2 [Control: M_{diff} = -.002, $SD_{diff f}$ = .104; Fatigue: M_{diff} = -.02, SD_{diff} = .12; $t(68) = .460$, $p = .647$] and pWIN r^2 [Control: M_{diff} = .003, SD_{diff} = .05; Fatigue: M_{diff} = .01, SD_{diff} = .05; $t(68) = .594$, $p = .555$]).

Cognitive fatigue reduces the stability of economic decision making

Post-hoc, we noticed a pattern of reduced test-retest correlations within the fatigue group across the economic decision making measures. To quantify this, we used a Fisher's r-to-z transformation to compare the pre- and post-correlations between fatigue and control groups for each metric (Table 4.4 and Figure 4.5).

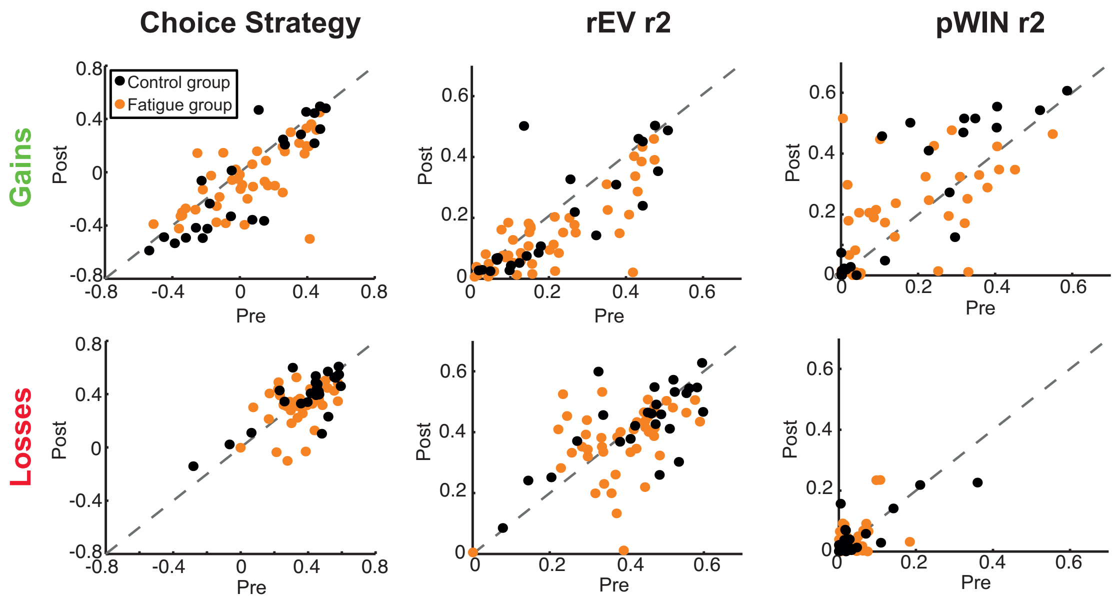

Figure 4.5. Choice strategies in the gains and losses domains. Relationship between pre- and post- manipulation independent R-squared values of (A) strategy, (B) rEV and (C) pWIN on trial-by-trial choice behavior for both fatigue and control groups.

Table 4.4. Test-retest correlations for uncertainty premiums and information strategy metrics in the gains and losses domains for controls and fatigued subjects.

	Control		Fatigue			
	r	*p*	*r*	*p*	*z*	*p*
Gains						
Uncertainty Premium						
Risk	.94	< .0001	.56	< .001	3.10	.002
Ambiguity	.69	< .01	.48	.011	.860	.389
Information strategy						
Choice strategy	.89	< .0001	.68	< .0001	2.07	.039
rEV r^2	.81	< .0001	.80	< .0001	0.11	.912
pWIN r^2	.70	< .0001	.60	< .0001	0.41	.682
Losses						
Uncertainty Premium						
Risk	.74	< .0001	.32	.039	2.24	.025
Ambiguity	.63	< .01	.41	< .01	1.13	.259
Information strategy						
Choice strategy	.77	< .0001	.41	< .001	2.29	.022
rEV r^2	.70	< .0001	.45	< .01	1.45	.147
pWIN r^2	.80	< .0001	.44	< .01	2.42	.015

r: correlation coefficient; *z*: Fisher's r-to-z transformation test for the significance of the difference between two correlation coefficients.

Cognitive fatigue reduces the stability of risk preferences

Risk premium values in the gains domain showed significantly lower test-retest correlations in the fatigue group than the control group ($z = 3.10$, $p = .002$). This effect was not found for the ambiguity premiums ($z = .86$, $p = .389$). The losses domain mirrored the results of the gains domain; risk premium test-retest correlations were significantly lower in the fatigue group than in the control group ($z = 2.24$, $p = .025$), with no difference for ambiguity premiums ($z = 1.13$, $p = .259$).

Cognitive fatigue reduces the stability of choice strategy

Choice strategy values, in both the gains and the losses domains, had significantly lower test-retest stability in the fatigue group than in the control group (gains, $z = 2.07$, $p = .039$; losses, $z = 2.29$, $p = .022$) (Table 4.4 and Figure 4.5).

Change in fatigue does not relate to individual change in economic metrics

It is possible that individual changes in fatigue or effort could account for individual differences in the economic metrics. For example, while there is no mean shift in risk preference across groups, it is still possible that there could be a linear relationship between individual change in fatigue and individual change in risk preference. To specifically test for this post-hoc, across all participants, we correlated the change in fatigue and effort against our economic metrics of risk preference, ambiguity preference, choice strategy, the rEV r^2, and the pWIN r^2, in both the gains and losses domains. We applied a full-Bonferroni correction ($p = 0.005$) to account for these 10 additional tests on each of our measures of individual fatigue and individual effort. None of these factors indicated a relationship that survived the necessary multiple comparison correction.

Individual effort/fatigue does not relate to individual change in economic metrics

We also post-hoc examined whether individual levels self-reported fatigue or effort (RSME) relate to changes in our economic measures (risk preference, ambiguity preference, the rEV r^2, and the pWIN r^2). Within each domain (gains or losses), we applied a full Bonferroni corrected threshold to p = .0125 for the 4 tests. None of the 8 correlations were significant.

Discussion

We examined how cognitive fatigue impacts economic decision making, focusing on uncertainty preferences (risk and ambiguity) and choice strategies in both the gains and losses domains. We found no mean shifts in preferences or strategies across either domain. Rather, post-hoc analyses revealed that cognitive fatigue resulted in decreases in test-retest stability across both risk preferences and choice strategies.

Cognitive fatigue reduces the stability of risk preferences

We found no mean shifts of uncertainty preferences (risk or ambiguity) due to cognitive fatigue. Rather, cognitive fatigue reduced the stability of risk preferences. When fatigued, subjects were inconsistent in their risk preferences, demonstrating more variable risk attitudes.

Multiple studies have suggested that suboptimal mental states are associated with increased intra-individual variability in performance measures such as reaction time (Habeck et al., 2004; Chee et al., 2006; Lim et al., 2004). Only one study, by Levy and colleagues (2013), has previously reported on altered within-subject variability in risk preferences due to a state manipulation, finding that food deprivation led to decreased variability in risk preferences. It is likely the case that alterations in decision making due to cognitive fatigue and food deprivation occur through different mechanisms, and it is interesting to see opposite effects on choice variability. These results highlight the importance of considering alterations in intra-individual variability in addition to the standard mean shifts.

In contrast to increased instability in risk preferences, we found no changes in ambiguity preferences. This finding appears to concur with neurobiological evidence that these two preferences may be dissociable (Huettel et al., 2006). However, it is not clear if our results should be taken as further evidence of such dissociation, as we also found weaker test-retest reliability for ambiguity within the control group (greater within-subject variability for ambiguity preferences), which would have limited our power for detecting alterations due to cognitive fatigue (see Table 4.4).

Cognitive fatigue reduces the stability of choice strategy

In both the gains and losses domains, fatigue reduced the stability of choice strategy without leading to mean shifts (i.e., a general shift towards more satisficing or maximizing behavior). It is quite interesting that this result mirrors the alterations we found for risk preferences, as risk preferences and choice strategy are not correlated across our participants, and ostensibly measure different aspects of decision making.

Of note, reduced effort in decision making is potentially an attractive explanation for how cognitive fatigue increased the noise in our choice strategy metric. However, such a motivational change would actually have presented as an increase in satisficing behavior (decreased choice strategy) – exactly the shift that we initially hypothesized and did not find. Rather, participants continue to, on average, employ the same relative levels of satisficing and maximizing strategies in their choice behavior, suggesting that they are maintaining their behavioral motivation in our incentive compatible tasks.

Implications and relation to a neural network of fatigue

Cognitive fatigue results in greater variability in both risk preferences and choice strategies, which will result in decreased consistency in the actual choices made. Insofar as choice quality can be simply judged based upon whether you would repeat your choice given the same options, these results indicate that cognitive fatigue reduces choice quality.

In relation to economic theory, inconsistent preferences or strategies may lead to failures of transitivity (if we prefer A to B and B to C, we should choose A over C) a key rule of rational choice behavior (von Neumann & Morgenstern, 1944). The implications of these results are that decisions made under cognitive fatigue are likely to result in more variable choices than those performed under a non-fatigued state, with the potential for regret when the chooser returns to a rested state. Concurring, in the field of strategic management 'judgment quality' describes the effectiveness of decisions with reduced response consistency indicating reduced judgment quality, and erratic decisions have been associated with less optimal results and economic inefficiency (Bowman, 1963; Karelaia & Hogarth, 2008; Hogarth & Makridakis, 1981). That individual alterations are unsystematic and unpredictable consequently make it harder to insure against these uncharacteristic and capricious decisions.

Interestingly, our results resemble the behavioral effects of ventromedial prefrontal cortex (vmPFC) damage, which leads to inconsistent or erratic preference judgements without a slowing of response times (Fellows & Farah, 2007; Henri-Bhargava, Simioni, & Fellows, 2012). This suggests that cognitive fatigue has a transient effect that results in alterations of behavior in ways similar to those with physical damage to their vmPFC. The vmPFC is further implicated in the production or subjective experience of cognitive fatigue, as individuals with focal lesions in the vmPFC reported significantly greater levels of fatigue as compared to individuals with lesions in other locations within the prefrontal cortex (PFC) (Pardini et al., 2010).

Maintained N-back task performance despite cognitive fatigue

Participants in the fatigue group maintained a high level of performance on the N-back task despite reporting increasing levels of fatigue and indicating that high levels of mental effort were required to perform each subsequent block.

This observed pattern of unchanged task performance under cognitive fatigue is not uncommon (Dobryakova et al., 2013). Surprisingly, despite the reliability in observing fatigue carry-over effects, primary time-on-task decrements are far less consistently seen, with success in inducing fatigue usually determined by its effects on the secondary task (Hockey et al., 2000; Robert & Hockey, 1997; Hockey, 2011). It is unclear whether this discrepancy may be mediated by the demands of the task that is used to induce fatigue. Shigihara and colleagues (2013) reported that while task performance was not diminished in 30 min of a 2-back task, performance decreased over time when participants performed the relatively easier 0-back task for the same amount of time. The authors suggest that mundane tasks may increase sleepiness, while more challenging tasks paradoxically increase motivation and lead to maintenance of high levels of performance. A future challenge may be to clarify which types of cognitive tasks are most affected by fatigue and to construct a unifying explanation of why certain tasks reveal a time-on-task effect while others remain impervious to fatigue.

Relating cognitive fatigue to other state alterations

It is unclear how cognitive fatigue relates to other state alterations, such as sleep deprivation, aging, or ego-depletion. A fruitful area for future investigations would be to investigate how various state alterations may share common mechanisms.

A priori, one may expect that there would be similarities between the effects of cognitive fatigue and sleep deprivation. In fact, there is a recent model of sleep deprivation effects, called 'the state instability hypothesis', whose name sounds strikingly similar to our found effects (Doran, van Dongen, & Dinges, 2001). This model posits that sleep-initiating mechanisms disrupt a person's capacity to maintain alertness, resulting in 'lapses' that occur briefly and are interspersed with otherwise normal performance capabilities. Such a model cannot account for the effects of our study, as the hypothesized effects would have been apparent in two ways in the comparison of the cognitive fatigue group to the control group, both of which were absent, 1) reduced R-squared values for either the rEV or pWIN (or both) and 2) reduced response times.

Our cognitive fatigue manipulation involved 60 to 90 minutes of a strenuous task that engaged executive control. A similar methodology, although involving only ~10% of the manipulation duration, occurs in ego-depletion manipulations (Baumeister et al., 1998). In ego-depletion studies, following the manipulation task, participants are presented with situations or tasks in which they would normally exercise willpower to exert self-control over their behavior. It is unclear how to conceptually relate cognitive fatigue and ego-depletion, but given the similar methodologies, it is interesting to consider their potential overlap. Baumeister (2002) hypothesized that ego-depletion should result in more impulsive consumer behaviors. No prior studies have tested this experimentally. Potentially, our current study may be considered to test and disprove this hypothesis. We note that there is controversy about the effectiveness of the ego-depletion manipulation, with the potential that participants' beliefs strongly influence the effect (Xu et al., 2014; Job et al., 2013).

Future directions

Of specific interest for future studies will be examining how cognitive fatigue may dissociably alter sub-components of the cognitive processes engaged during economic decision making. As we find a general effect across economic decision making metrics, this suggests that cognitive fatigue is altering cognitive processes that are engaged across these economic metrics. Possible examples include interfering with working memory, preventing memory consolidation of prior choices, interfering with the application of preferences, or interfering directly with the comparison process.

There is potentially great utility in examining and comparing how varied state modulations commonly and dissociably alter economic decision making. For example, in these same tasks, we recently showed that aging produces specific shifts of risk preferences and strategies in the losses domain, without altering these processes in the gains domain (Kurnianingsih et al., 2015).

The duration of our cognitive fatigue manipulation (60 to 90 minutes) was specifically aimed at examining a duration that is common in everyday life. It is unclear if longer durations of cognitive fatigue will result in specific shifts in economic preferences, such as enhanced/reduced risk aversion or reduced use of maximizing information. However, we saw no significant differences between the 5-blocks and 7-blocks cognitive fatigue groups (60 and 90 minutes, respectively).

Conclusions

The results of this study show that cognitive fatigue results in destabilization of risk preferences and the informational strategies participants employ. This increased variability in choice behavior can undermine the integrity of decisions, resulting in diminished choice behavior quality.

Chapter 5: Divergence and convergence of risky decision making across prospective gains and losses[7,8]

The previous three chapters demonstrate differential modulation of economic decision making by three different state modulations: 1) aging, 2) sleep deprivation and 3) cognitive fatigue. Clear behavioral dissociations between these three state modulations were found. The gains and losses domains were differently affected, especially by aging and sleep deprivation. Interestingly, across the three studies, we found no relationship between gains and losses risk preferences. This was the base motivation for performing this next study that tested the relationship between gains and losses risk preferences. We specifically looked at the relationship between gains and losses risk preferences, how well cross-domain risk preferences could inform individual choice behavior, and risk preference relation to choice strategy using a gains and losses intermixed-trial design and a larger sample of young healthy adults.

Abstract

People choose differently when facing potential gains than when facing potential losses. Clear gross differences in decision making between gains and losses have been empirically demonstrated in numerous studies (e.g.

[7] This paper has been previously published: Kurnianingsih, Y.A. & Mullette-Gillman, O.A. (2015) Divergence and Convergence of Risky Decision Making Across Prospective Gains and Losses: Preferences and Strategies. Front. Neurosci. 9:457. doi: 10.3389/fnins.2015.00457
[8] Contributions: YA and OAMG designed the experiment, analyzed the data and wrote the manuscript. YA collected the data.

framing effect, risk preference, loss aversion). However, theories maintain that there are strong underlying connections (e.g. reflection effect). We investigated the relationship between gains and losses decision making, examining risk preferences and choice strategies (the reliance on option information) using a monetary gamble task with interleaved trials. For risk preferences, participants were on average risk averse in the gains domain and risk neutral/seeking in the losses domain. We specifically tested for a theoretically hypothesized correlation between individual risk preferences across the gains and losses domains (the reflection effect), but found no significant relationship in the predicted direction. Interestingly, despite the lack of reflected risk preferences, cross-domain risk preferences were still informative of individual choice behavior. For choice strategies, in both domains participants relied more heavily on the maximizing strategy than the satisficing strategy, with increased reliance on the maximizing strategy in the losses domain. Additionally, while there is no mathematical reliance between the risk preference and strategy metrics, within both domains there were significant relationships between risk preferences and strategies – the more participants relied upon the maximizing strategy the more risk neutral they were (equating value and utility maximization). These results demonstrate the complexity of gains and losses decision making, indicating the apparent contradiction that their underlying cognitive/neural processes are both dissociable and overlapping – potentially the result of both divergent and convergent evolutionary pressures.

Introduction

The purpose of decision making is to select the best possible outcome. Broadly, decision making can be divided into two overlapping types – those with potential gains and those with potential losses. While mathematically the sign makes little difference, there is abundant behavioral evidence that quite different cognitive processes may be engaged when outcomes pertain to possible gains vs. possible losses. As a powerful example, simply altering the wording of the same absolute outcome between a relative gain and a relative loss produces stark differences in choices, a phenomenon called the framing effect (Tversky & Kahneman, 1981).

While it is clear that decision making is different between gains and losses, it is unclear what specifically is altered. For example, these differences could be due to alterations in risk preferences or alterations in the information that participants rely upon to make their decisions (their choice strategy).

When faced with probabilistic outcomes (uncertainty), individuals, on average, show differential preferences when choosing between possible gains and possible losses. In prospect theory, individuals are considered on average risk averse for gains (prefer smaller certain rewards to larger uncertain rewards) and risk seeking for losses (prefer a larger possible loss over a smaller certain loss) (Kahneman & Tversky, 1979). This pattern of inverted preferences over the gains and losses domains is called the reflection effect, and has been suggested to derive from risk preferences arising from each individual having a common degree of diminishing weight of marginal utility across both gains and losses. This single value (the power function risk preference value) would result in differential behavior across gains and losses, as individuals are drawn towards higher gains and away from higher losses.

It is unclear whether the reflection effect actually occurs within individuals, or is only present when comparing group averages. If present in an individual, then there should be a fixed relationship between risk preferences for gains and risk preferences for losses (negatively correlated, e.g. individuals who are most risk averse for gains should be most risk seeking for losses) and an individual’s risk preferences from one domain should be predictive of their risk preference in the other. When empirically tested, the reflection effect has been found in individuals when using hypothetical payoffs (Laury & Holt, 2000), but not with real cash payouts (Cohen et al., 1987; Schoemaker, 1990; Laury & Holt, 2000; Tymula et al., 2013; Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015a; Mullette-Gillman et al., 2015b). It has recently been suggested that the theoretical reflection effect of risk preferences across the gains and losses domains may be the product of studying aggregate behavior and does not exist at the level of individual behavior (Tymula et al., 2013).

The changes in choice behavior between the gains and losses domains may also be due to changes in the strategies individuals employ (what information they use to make their decision). For example, individuals can either attempt to maximize their expected outcomes by fully engaging with the available information, or they may satisfice to reduce the expended effort while sacrificing expected outcomes. The differences in how individuals utilize available information may be influenced by sensitivity towards gains and losses. Loss aversion is a key example of this, in which individuals tend to weight choices more heavily on possible losses (Tversky & Kahneman, 1992), and has been suggested to increase motivation in choice behavior (McCusker & Carnevale, 1995), which can be expressed in the use of a more effortful strategy (requiring more calculation) as they attempt to maximize the expected outcome. Alternatively, Schneider (1992), using hypothetical non-incentivized scenarios, suggested that choices were less consistent when described in a loss frame.

Differential processing of gains and losses is also supported by biological evidence indicating that the underlying neural computations may be separable (for review, see Levin et al., 2012). As examples, 1) amygdala lesions result in impaired decisions for gains but not losses (Weller et al., 2007), 2) numerous brain regions involved in decision making show differential responses to gains and losses – including the orbital frontal cortex, midbrain, ventral striatum and hippocampus (Elliott et al., 2000; Luking & Barch, 2013), 3) aging results in asymmetric alterations of gains and losses risk preferences (Mikels & Reed, 2009; Weller et al., 2011; Kurnianingsih et al., 2015), 4) sleep deprivation modulates risky decision making strategies for gains, but not for losses (Mullette-Gillman et al., 2015b), and 5) affect manipulations differentially modulate choices across the gains and losses domains (Isen, et al., 1988).

Although such ample evidence shows clear differences between choice behaviors and neural responses in the gains and losses domains, it remains unclear what cognitive processes / neural mechanisms actually drives these differences. To investigate this, we used a monetary gamble task to examine the interrelationships of risk preferences and choice strategies across the gains and losses domains. Critically, we used mirrored and intermixed gains and losses trials, to avoid any potential order or block effects. Our hypotheses were: 1) on average, individuals would be risk averse in the gains domain and risk seeking in the losses domain, 2) individual risk preferences would be uncorrelated across the gains and losses domains, 3) individuals would show higher use of the more effortful and maximizing strategy in the losses domain than in the gains domain. In addition, we examined the predictive power of cross-domain risk preferences on choice behavior and also the interrelationship between risk preferences and choice strategies within and across the gains and losses domains

Materials and methods

Participants

Data was collected from 104 participants (57 females, mean ± SD age = 23 ± 2.47 years old) that were students from the National University of Singapore. All participants provided written informed consent under a protocol approved by the National University of Singapore Institutional Review Board.

Monetary gamble task design

Risk preference and choice strategy measures were quantified based on participant's performance on a monetary gamble task. Data collection and analyses were accomplished using MATLAB (Mathworks, Natick, MA) with the Psychophysics Toolbox for trial presentation (Brainard, 1997), and R Statistical Software (R Core Team, 2013).

The monetary gamble task consisted of 165 gains trials and 165 losses trials (Figure 5.1A). On each trial, participants chose between a certain option and a gamble option. All gambles featured a possible $0 outcome, to provide a clear and consistent anchor point across all trials, to ensure the frame in which participants considered the possible outcomes (Tversky and Kahneman, 1974). Within the gains trial, there were five different certain gain options {$3, $4, $5, $6, $7}. Gain gambles were constructed based upon three probabilities of winning (pWIN, which are {25%, 50%, 75%}), and eleven different relative expected values (rEV or $EV_{Gamble}/ V_{Certain}$, which are {0.25, 0.33, 0.50, 0.66, 0.80, 1.0, 1.25, 1.5, 2.0, 3.0, and 4.0}). These probabilities and relative expected values resulted in potential gains ranging from $1 to $112. The losses trials were constructed using the same method and values, save for mirroring the valence of the values offered into negatives. The trial order was fully randomized separately for each participant, intermixing gains and losses domain trials.

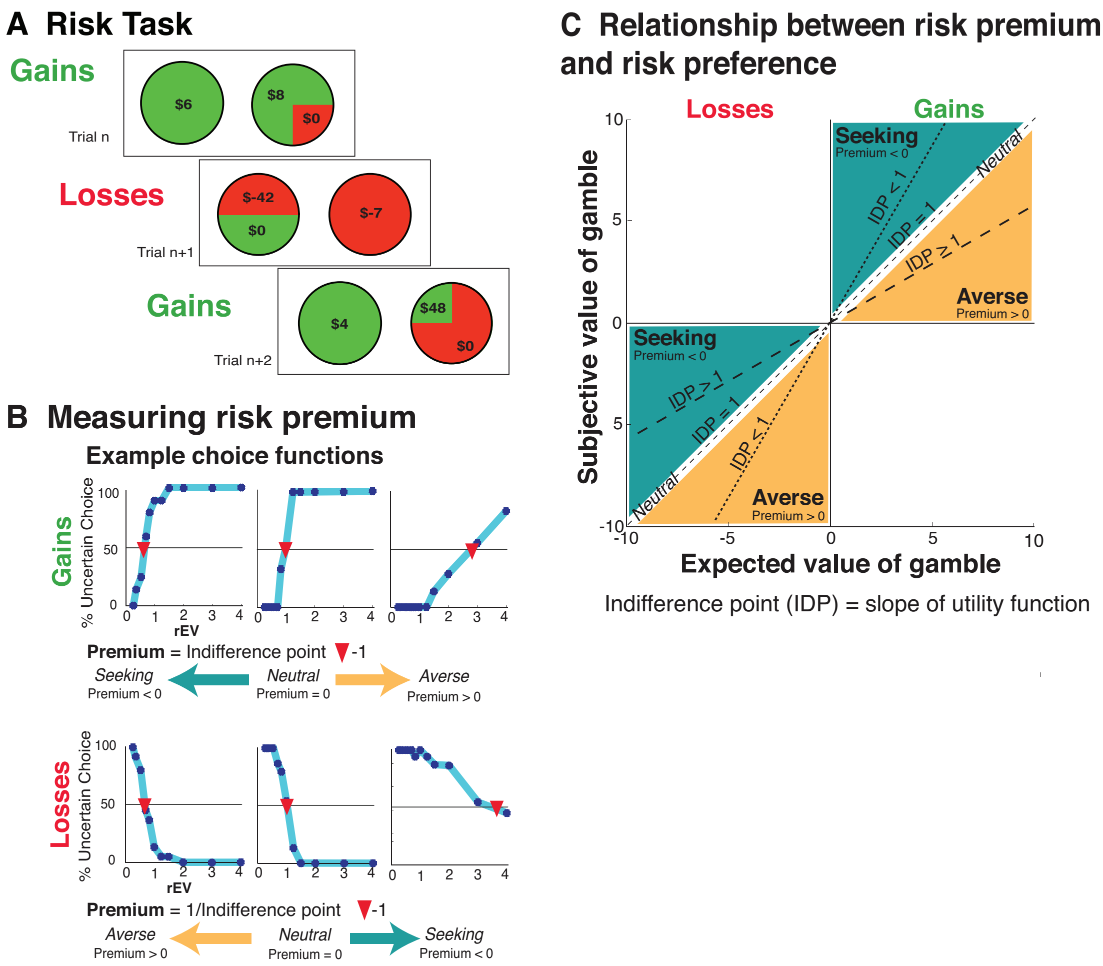

Figure 5.1. (A) Example task trials. In each trial, participants chose between a certain and a risky option. There were two types of trials, the gains and losses trials, randomly intermixed. (B) Example individual choice functions for six individuals (top: 3 for gains, bottom: 3 for losses). Choice functions were plotted within each domain for each participant. Each relative expected value (x-axis) was plotted against the percentage of trials (out of 15 for each point) at which the participant selected the risky option (y-axis). (C) An illustration describing the relationship between the relative expected value of the gamble (x-axis), the subjective value of the gamble (y-axis) and risk premium (slope of the lines).

Before performing the task, participants were informed that the amount of their compensation for participation would be between \$5 and \$25, based upon a non-revealed proportion of the total monies that they collected from random selection and resolution of one trial from each domain at the end of the experiment. Unbeknownst to the participant, the final percentages were 50% for the gains task and 25% for the losses task, with the differential to help ensure positive compensation to the participants. On average, participants received \$7.77 (SD = \$4.22; min = \$5.00 and max = \$25.00).

Critically, our design features multiple safeguards to prevent potential order, learning, or framing confounds. To prevent order and/or block effects, gains and losses trials were randomly intermixed. To prevent alterations of preferences and/or strategies due to inter-trial learning, no gambles were resolved until the completion of the experiment. To prevent framing confounds, all gambles feature a \$0 outcome to provide a clear common anchor across trials.

Quantifying risk preferences

Risk preferences are commonly quantified using a variety of methodologies. In economics, risk preference is often conceptualized as the curvature of the value-to-utility function (a power function) due to diminishing marginal utility, based upon expected utility theory (von Neumann & Morgenstern, 1944), and prospect theory (Kahneman & Tversky, 1979). Risk preference has also been quantified as the degree of variance of the expected value (Markowitz, 1952; Bossaerts & Plott, 2004) measured using the coefficient of variation (CV), which is calculated as the ratio of the standard deviation to the expected value of the gamble (Weber et al., 2004).

In psychology, risk-taking behavior has been examined using a large range of tasks and models, including the Iowa Gambling Task (IGT; Bechara, et al., 1994), the Balloon Analogue Risk Task (BART; Lejuez et al., 2002), and the Cambridge Gamble Task (CGT; Rogers et al., 1999). In such tasks, risk preference is often quantified by the proportion of times the participant chooses the riskier option.

As a midpoint, in this study we used a model free psychometric approach to empirically examine risk preferences (Stanton et al., 2011; Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015a; Mullette-Gillman et al., 2015b). This method quantifies risk preference (in each domain) as a risk premium metric, which measures the degree to which people appear to alter the subjective value of gambles due to outcome uncertainty. In addition, to facilitate comparison with studies from economics and test the robustness of our analyses/results, we replicated analyses utilizing the power function metric.

Risk premium metric. To quantify this psychometric measure of risk, choice functions were constructed by plotting a continuous function based upon the percentage of gamble selection (y-axis) for each respective examined rEV (EV_{Gamble}/ $V_{Certain}$) (Figure 15.B). This identifies the point along the rEV axis at which the participant is indifferent between the certain and gamble options (Stanton et al., 2011; Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015a; Mullette-Gillman et al., 2015b). This indifference point is then converted to a risk premium value. In the gains domain, the risk premium is generated by subtracting 1 from the indifference point value (risk premium = indifference point - 1). In the losses domain, as the rEVs are relative to the absolute values, the risk premium is obtained by first inverting the indifference point value before subtracting 1 (risk premium = 1/indifference point - 1).

The risk premium value measures the degree and direction in which an individual modulates the subjective value of a gamble due to the outcome being unknown (Figure 5.1C). For example, a risk premium value of 1 indicates that the individual requires a gamble to have an expected value twice that of a certain option in order to find the two options equivalent. In other words, they are subjectively halving the expected utility of the gamble due to uncertainty. For both domains, a zero risk premium value reflects no change in valuation (risk neutral), a positive risk premium value denotes diminished valuation (risk averse) and a negative risk premium value denotes enhanced valuation (risk seeking).

We note that participants presented highly monotonic choice functions, as exemplified by the six presented in Figure 5.1B. A small number of participants had choice functions that did not cross the 50% uncertain choice, preventing us from calculating their indifference point (gains N = 13, losses N = 5). Such participants were excluded from analyses of their risk premium values. We note that the majority of such participants did not show extreme risk preferences with monotonic choice functions, but rather demonstrated dependence on simple heuristics (such as always choosing the certain option, or always choosing certain for one probability and gamble for others), resulting in choice functions that were flat across our examined range of rEV values, and placing their behavior outside of our functional definition of risk preference. We note that such behavioral heuristics are well-captured by our strategy analyses.

Power function metric. We also independently computed the power function metric of risk preference for each domain (based on Tymula et al., 2013).

For gains (if V>0): $SV = pWIN \times V^{\alpha}$

For losses (if V<0): $SV = -(1-pWIN) \times (-V)^{\alpha}$

where SV is the subjective value (utility), pWIN is the probability of receiving the better outcome of the gamble, V is the potential objective value offered and α is the participant's risk preference value. In the gains domain, $\alpha < 1$ indicates risk averse preference, $\alpha = 1$ indicates risk neutral preference, and $\alpha > 1$ indicates risk seeking preference. In the losses domain, the relationship is inverted, such that, $\alpha < 1$ indicates risk seeking preference, and $\alpha > 1$ indicates risk averse preference.

To estimate individual's risk preference, we used maximum likelihood to fit the choice data of each participant with the probability choice function (Tymula et al., 2013):

Probability of choosing the gamble option = $\frac{1}{1+e^{-(SV_G - SV_C)}}$

where SV_c is the subjective value of the certain option and SV_G is the subjective value of the gamble option.

We have previously reported strong correlations (r > |.6|) between our risk premium metric and the power function metric (Stanton et al., 2011;

Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015a; Mullette-Gillman et al., 2015b), and find similar results in the current sample (see Results).

Quantifying choice strategy

Choice strategy measures the influence of trial factors on the choices of each participant, as quantified through the use of linear regressions. Analyses were conducted separately within the gains and losses domains, through independent linear regressions to determine the influence of two factors on the choices of each participant: 1) the relative expected value (rEV) of the options, and 2) the probability of winning (pWIN) the gamble option. The R-squared value of each factor gives us a measure of the proportion of individual's choice variance (across trials within domain) accounted for by each factor. Therefore a high R-squared value for rEV or pWIN would indicate that choices could be well-accounted for based on that specific trial information (e.g. a participant that accepts all gambles with a 75% chance of winning would have a high pWIN R-squared value, and a participant that accepts gambles with an rEV equal or higher than 1 would have a high rEV R-squared value), whereas a low R-squared value would indicate that choices were more likely based on other factors (or were made randomly). It is important to note that based on task design, the pWIN and rEV trial values are orthogonal to each other (the correlation between trial rEV and trial pWIN across all trials is zero). In addition, we note that while we chose to focus on the rEV factor, in this task this factor is essentially isometric with the difference in expected values (for both gains and losses domains, $r(102) = .99$,

$p < .0001$) and is uncorrelated with pWIN (gains $r(102) = -.44$, $p < .0001$; losses $r(102) = -.50$, $p < .0001$).

Participants were considered to be ‘maximizing’ when they relied highly on the rEV information and ‘satisficing’ when they relied highly on the pWIN information. The utilization of the rEV information maximizes average outcomes but requires several layers of effortful cognitive calculation, while focusing on the pWIN information allows the use of simple heuristics requiring less cognitive effort.

Measuring individual numerical ability

The ability to understand and perform simple mathematical calculations was assessed using an 8-item Numeracy Scale developed by Weller and colleagues (2013). This assessment was given to the participants after they had completed the gamble task, but before resolution of the payments for the choices were made for the gamble task.

Measuring behavioral impulsiveness

Behavioral impulsiveness was assessed using The Barratt Impulsiveness Scale (BIS-11, Patton & Standford, 1995). Impulsivity has been considered as a factor influencing risk-taking behaviors (Zaleskiewicz, 2001; Zuckerman, 2007). The 30-item BIS-11 questionnaire consists of three subscales – cognitive, non-planning and motor. The sum of the subscale scores provides us with a general measure of individual overall impulsiveness. Participants completed this survey after completion of the gamble task, but before resolution of the payments for the choices were made for the gamble task.

Results

Response time

As a first comparison of decision behavior between the gains and losses domains, we compared response times between gains and losses trials (see Table 1 for summary of the results). We found that on average, response time were longer for trials in the losses domain (*mean of individual medians* ± *SD* difference = .89 ± .54s, gains = 1.90 ± .68s, losses = 2.79 ± 1.00s; $t(103) = 16.58$, $p < .0001$, Cohen's $d = 1.04$).

Risk preferences

Correlations across risk premium and power metrics. To facilitate cross-analytic approaches, we compared the model-free risk premium metric to the model-based risk preference parameter from the power utility function. We found very high correlations between these two risk preference metrics in both the gains ($r(89) = -.65$, $p < .0001$) and the losses domains ($r(96) = .58$, $p < .0001$), in concurrence with our prior studies (Stanton et al., 2011; Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015a; Mullette-Gillman et al., 2015b). These high correlations indicate that the risk premium and power function metrics are largely capturing the same variance across participants. To confirm this similarity and the robustness of our results, for each analysis we provide the results using both the risk premium and power function metrics.

Average risk preference. Participants were, on average, risk averse in the gains domain (risk premium *mean* ± *SD* = .44 ± .70; significantly different from 0, $t(90) = 6.05$, $p < .0001$, $d = .64$) and risk neutral in the losses domain (risk premium *mean* ± *SD* = .06 ± .30; not significantly different from 0, $t(98) = 1.97$, $p = .052$, $d = .20$) (Figure 5.2). Utilizing the power function metric, we replicated the above pattern of results (Table 5.1). Individuals were on average risk averse for gains (*mean* ± *SD* = .68 ± .22; significantly different from 0, $t(103) = 14.84$, $p < .0001$, $d = 1.47$) and weakly risk seeking for losses (*mean* ± *SD* = .95 ± .26; significantly different from 0, $t(103) = 2.06$, $p = .04$, $d = .20$), with Cohen's *d* indicating small effect size for losses (Cohen, 1988).

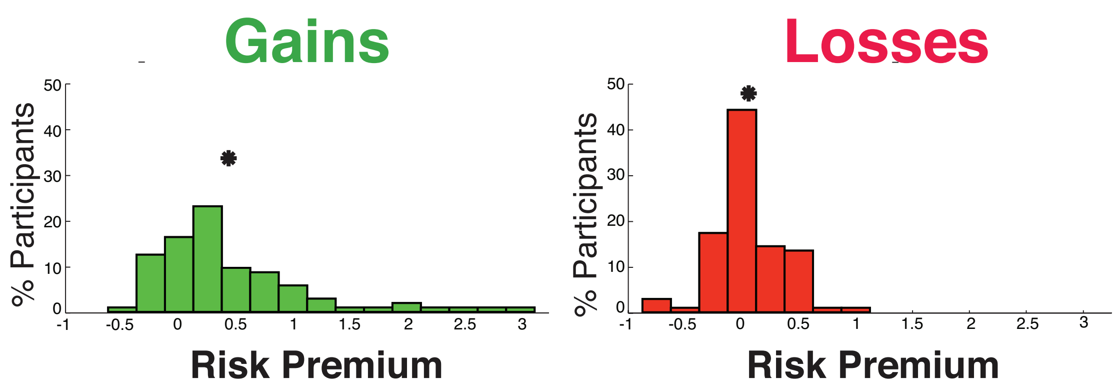

Figure 5.2. Risk premium distribution across participants in the gains domain and losses domain. The asterix indicates the mean value of each distribution.

Table 5.1. Comparing economic measures between the gains and losses domains

	Gains Domain	Losses Domain	Correlation		t-test		z-test	
	mean ± SD	*mean ± SD*	*Coefficient (r)*	*p-value*	*t-score*	*p-value*	*z-score*	*p-value*
Response Time (s)*	.901 ± .675	2.786 ± 1.003	.860	< .0001	16.58	< .0001		
Risk Preference								
a) Risk Premium	.441 ± .695	.059 ± .296	.153	.156	5.89	< .0001		
(91, 99)**	.684 ± .217	.984 ± .259	.084	.395	8.30	< .0001		
b) Power Function	r = -.648,	r = .583,					.71	.478
(96, 101)	p < .0001	p < .0001						***
Correlation between								
a and b			.608	< .0001	3.41	< .0001		
	.338 ± .169	.383 ± .117	.242	.013	1.02	.310		
Choice Strategy	.042 ± .061	.035 ± .050					.50	.617
c) rEV R-squared	r = -.443,	r = -.498,						
(104, 104)	p < .0001	p < .0001						
d) pWIN R-squared							2.19	.029
(104, 104)							1.42	.156
Correlation between	r = -.143,	r = -.436,						
c and d	p = .177	p < .0001						
	r = .041,	r = .246,						
Preference ×	p = .700	p = .014						
Strategy								
e) Premium × rEV								
R-squared								
f) Premium × pWIN								
R-squared								

* For response times, median is provided instead of mean.
** Numbers in parentheses indicate the number of participants (Gains, Losses).
Abbreviations: rEV, relative expected value; pWIN, probability of winning; s, seconds; SD, standard deviation.
*** Given the differential relationships between the premium and power metrics across the gains and losses domains, the sign of the correlation in gains was inverted to allow for comparison (comparing correlation of .648 to .583)

Testing for non-parametric relationships between risk preferences across domains. To begin our examination of whether the reflection effect extends from average risk preferences to individual risk preferences, we followed the analysis of Tymula and colleagues (2013) by conducting a chi-square test to examine if there was evidence of a gross categorical relationship between individual risk preferences for gains and losses. This analysis groups participant based on whether they were risk averse or risk seeking in each domain (Figure 5.3).

Utilizing the risk premium metric, we found no significant relationship across risk preferences across domains ($\chi^2(1) = 2.52$, $p = .11$), with only 52.9% of the participants showing the pattern of preferences predicted by the reflection effect, indicating no significant relationship between risk preferences across domains. Utilizing the power function metric, 61.5% of the participants had categorical risk preferences in agreement with the reflection effect, which produced significance when examined using the chi-square ($\chi^2(1) = 5.51$, $p = .019$). Combined, these results show that the reflection effect is only weakly able to provide categorical prediction of risk preferences.

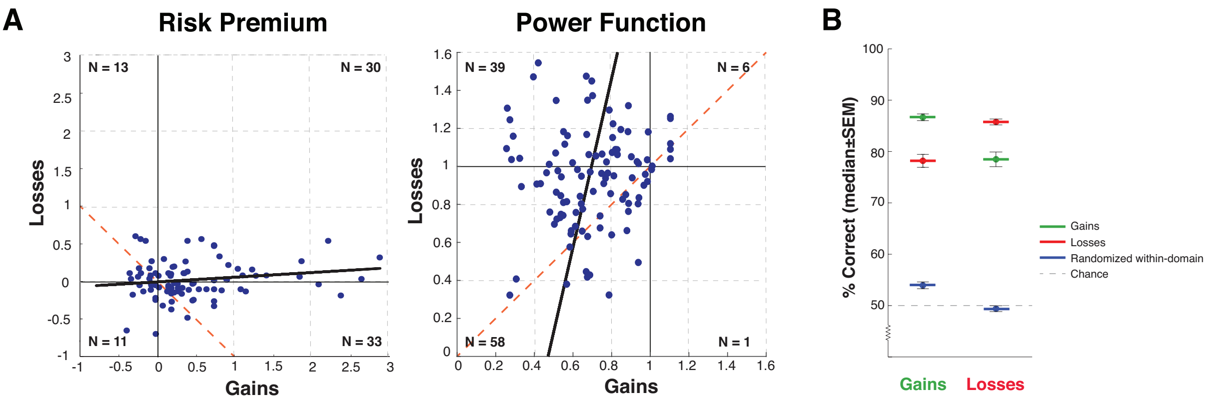

Figure 5.3. (A) Relationship of within-subject risk premium values across the gains and losses domains. The dashed red line visualizes the correlation predicted by the theoretical reflection effect, with a slope of -1 for the risk premium metric (left) and +1 for the power function metric (right). **(B) Cross-domain predictive comparison, percentage of choice behavior correctly predicted by each risk preference, across both domains.** Randomized

within-domain power function values were obtained through bootstrap analysis, randomly resampling risk preference value and participant's choice sets independently (N = 10,000 iterations, with replacement). The standard error measurement (SEM) value is the median SEM across iterations.

Testing for parametric relationship of risk preferences across domains. The reflection effect predicts a negative correlation between gains and losses risk premiums and a positive correlation between gains and losses power function (Figure 5.3). We found non-significant positively-signed correlations between the gains and losses domains, for both the risk premium ($r(85) = .15$, $p = .16$) and power function metrics ($r(102) = .08$, $p = .39$). This clearly indicates that the reflection effect is not detectable at the individual level. We note that, in concurrence with the finding of Tymula and colleagues (2013), we find effects in the opposite direction to that predicted by the reflection effect for the risk premium metric.

Modeling risk preferences across domains. To empirically identify the relationships between individual risk preferences across the gains and losses domains, we utilized linear regressions to identify the strength and direction of the predictive relationship.

For the risk premium metric, the reflection effect predicts that the losses risk premium value of each participant can be predicted based upon a transform of the gains risk premium value of that participant:

Predicted losses risk premium = 1/(gains risk premium+1) - 1

This is a slightly non-linear transform, which will result in the expected relationship between the gains risk premium and the transformed gains risk premium being dependent upon the distribution under examination. In the current sample, the reflection effect predicts a correlation of -.85. Using a linear regression to test for the presence of this relationship, we found a non-significant regression equation ($B_{Intercept}$ = -.005, p = .88; B_{Slope} = .055, p = .16) with an R-squared value of .023, indicating no evidence for the presence of an individual reflection effect using the risk premium metric.

For the risk power function metric, the reflection effect predicts that losses risk power function values should be equal to gains risk power function values (B_{Slope} = 1). Using linear regression yielded a solved equation with a significant intercept, but a non-significant slope ($B_{Intercept}$ = .88, $p < .0001$; B_{Slope} = .10, p = .40) with an R-squared value of .007. This does not agree with the theoretical reflection effect, as the significance found for the intercept suggests that alterations in risk preferences across the gains and losses domains are due to additive effects, while the theoretical reflection effect is multiplicative. Finally, the very low overall R-squared value indicates the lack of a meaningful predictive relationship between the gain and loss values.

In summary, using both the risk premium and risk power function metrics, we find no evidence for the presence of an individual reflection effect – gains risk preferences cannot predict losses risk preferences.

Empirically testing the predictive ability of cross-domain preferences. Without a significant within-subject relationship between risk preferences across the gains and losses domains, an important question is whether there is any predictive power through which cross-domain preferences can predict individual choice behavior. To test this, we calculated the within-subject proportion of choices that were predicted by each domains preference for each domains choices (2×2; gains preference predicting gains choices, gains preference predicting losses choices, losses preference predicting gains choices, and losses preference predicting losses choices). The cross-domain prediction measures the proportion of choices predicted by cross-domain preference assuming the reflection effect was true. We chose to limit this analysis to the power function metric, given multiple comparison concerns and the slight non-linearity across the gains and losses domains in the risk premium metric.

To guide interpretation, we determined two reference values for comparison. The first reference was chance, which definitionally is set at 50% (given the two-alternative choice task used). The second reference value accounted for behavioral regularities across participants engaged in this task, by examining scrambling the relationship between individual preferences and individual choices.

This second reference value, the randomized within-domain, was computed (for each domain) based on overall subject behavior in this domain, but with the specific removal of the relationship between individual preferences and individual choice behaviors. In other words, this reference value reflects that there may be regularities in the choice behavior across participants in this task, such that knowledge of any participant's choices may facilitate prediction of another participant's choices. To accomplish this, we ran two bootstrap analyses of 10,000 iterations (one for gains, one for losses).

In each iteration, we constructed a new sample of participants (N = 104), with replacement, by randomly selecting a preference value and then, independently, randomly selecting a choice set. Doing so specifically breaks the relationship between individual preferences and the actual choice behaviors. For each constructed participant, we then determined the proportion of choices in the randomly-selected choice set that could be predicted by the randomly-selected preference value. For each iteration, we took the mean proportion of choices correctly predicted across that sample. The median proportion across samples (N = 10,000), is our second reference value, the randomized within-domain – the proportion of trials that can be expected to be predictable based on knowledge of how participants behave (on average) in the task without specific knowledge of the participants preference value (essentially, removing all within-subject information). In the gains domain, the median value was 53.94% (*SD* = 8.86%) and in the losses domain the median value was 49.39% (*SD* = 6.03%). Comparing the two different reference values, in the gains domain the second reference was slightly higher than chance ($t(103) = 6.45$, $p < .0001$, $d = .63$), while in the losses domain, there was no significant difference between the two reference values ($t(103) = .67$, $p = .50$, $d = .07$).

The purpose of this analysis was to directly test how well individual preference values are able to predict behavior cross-domain (see Figure 3B). Within the gains domain, an individual's gains risk preference could account for a median of 86.67% (*SD* = 6.67%) of their choice behavior. Within losses, an individual's losses risk preference could account for a median of 85.76% (*SD* = 5.80%) of their choice. Across domains, we see that an individual's risk preference for gains accounts for a median of 78.48% (*SD* = 14.54%) of their choice behavior in the losses domain. Similarly, an individual's risk preference for losses accounts for a median of 78.18% (*SD* = 12.76%) of their choice behavior in the gains domain.

Contrasting these values, we see that a participant's within-domain risk preferences are always better predictors of their choices compared to their cross-domain risk preferences (see Table 5.2; paired-comparison t-tests Gains: $t(103) = .87$, $p < .0001$, $d = .96$; Losses: : $t(103) = 7.59$, $p < .0001$, $d = .92$). Interestingly, cross-domain risk preferences are able to predict participant's choices significantly better than the two reference values (all one-sample t-tests $t > 10.88$, $p < .0001$).

Table 5.2. Proportion of choices correctly predicted by each domain preference and reference in each domain

	Gains Domain		**Losses Domain**		**Across Domain t-test**	
	mean% ± SD%		*mean% ± SD%*		*t-score*	*p-value*
a) Gains preference (104)*	85.20 ± 6.67		75.02 ± 14.54		7.53	< .0001
b) Losses preference (104)	75.49 ± 12.76		85.19 ± 5.80		7.59	< .0001
c) Randomized within-domain preference**	55.60 ± 8.86 *median* = 53.94		49.60 ± 6.03 *median* = 49.39		> 100	< .0001
Within Domain t-test	*t-score*	*p-value*	*t-score*	*p-value*		
a and b	7.53	< .0001	7.59	< .0001		
a and c	45.28	< .0001	15.91	< .0001		
a and 50% chance	53.83	< .0001				
b and c	17.84	< .0001	62.59	< .0001		
b and 50% chance	6.45	< .0001	61.87	< .0001		
c and 50% chance			.677	.500		

* Number in parentheses indicates the number of participants.
** The relationship between individual preference and choice behavior was removed, and new samples (each N = 104, with replacement) were reconstructed through random selection of risk preference value and independent random selection of choice set (bootstrap analysis, with N = 10,000 iterations). The values of the bootstrap analysis stated above are the median of the mean and the median of the standard deviation from the 10,000 iterations.

Choice strategy

To examine which information each participant used to make their choices, we quantified the degree to which each participant relied on the trial rEV and pWIN information, as the amount of choice variance that could be explained by each factor (Figure 5.4). In the gains domain, participants relied more on the use of rEV information (*mean* ± *SD* rEV R-squared = .34 ± .17) than pWIN information (*mean* ± *SD* pWIN R-squared = .04 ± .06; $t(103) = 14.82$, $p < .0001$, $d = 2.34$) , with a negative relationship between the amount of rEV and pWIN information used ($r(102) = -.44$, $p < .0001$). A similar pattern was found in the losses domain, with higher reliance on rEV information (*mean* ± *SD* rEV R-squared = .38 ± .12, pWIN R-squared = .04 ±

.05; $t(103) = 23.81$, $p < .0001$, $d = 3.87$) and a negative relationship between the amount of rEV and pWIN information used ($r(102) = -.50$, $p < .0001$).

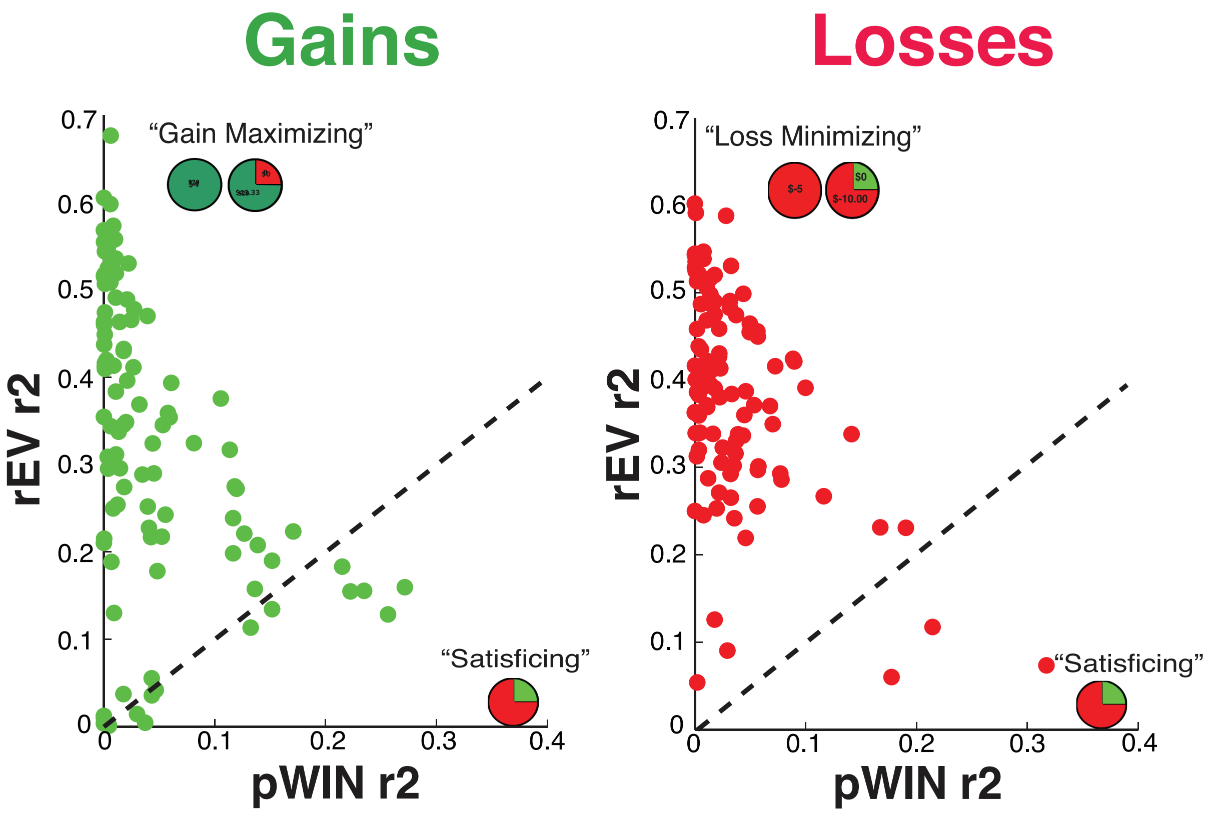

Figure 5.4. Choice strategy metric showing the relationship between the amount of trial relative expected value information and trial probability of winning information utilized. The R-squared value quantifies the amount of choice variances that can be independently explained by each trial factor, relative expected value (rEV) and probability of winning (pWIN).

Across domains, participants relied more on rEV information in the losses domain ($t(103) = 3.41$, $p < .0001$, $d = .31$), while there was no difference in the amount of pWIN information used ($t(103) = 1.02$, $p < .0001$, $d = .12$). Across domains, there were significant correlations in the amount of rEV and pWIN information participants used (rEV: $r(102) = .61$, $p <.0001$; pWIN: $r(102) = .24$, $p = .013$).

Relationship between risk premium and choice strategies

We investigated the relationship between the risk preferences and choice strategies within the gains and losses domains (Figure 5.5A and B; Table 5.1). We opted to limit these analyses to the risk premium metric, due to multiple comparison concerns, the high correlations between the premium and power function metrics, and our prior use of the premium to examine this issue in a study with blocked trials (Kurnianingsih et al., 2015). Within each domain, we looked separately for correlations between the risk premium and the two choice strategy components, rEV R-squared and pWIN R-squared. In the gains domain, we found no correlation between risk premium and the amount of rEV information used ($r(89) = -.14$, $p = .18$) or the amount of pWIN information used ($r(89) = .04$, $p = .70$). In the losses domain, we found significant correlations between the risk premium metric and both the amount of rEV information used ($r(97) = -.44$, $p < .0001$) and the amount of pWIN information used ($r(97) = .25$, $p = .014$). Comparing these correlations across domains, the correlation between risk premium and the amount of rEV information used was significantly stronger in the losses domain ($z = 2.25$, $p = .025$), while there was no significant change in the strength of the correlations between risk premium and amount of pWIN information used across domains ($z = 1.42$, $p = .16$).

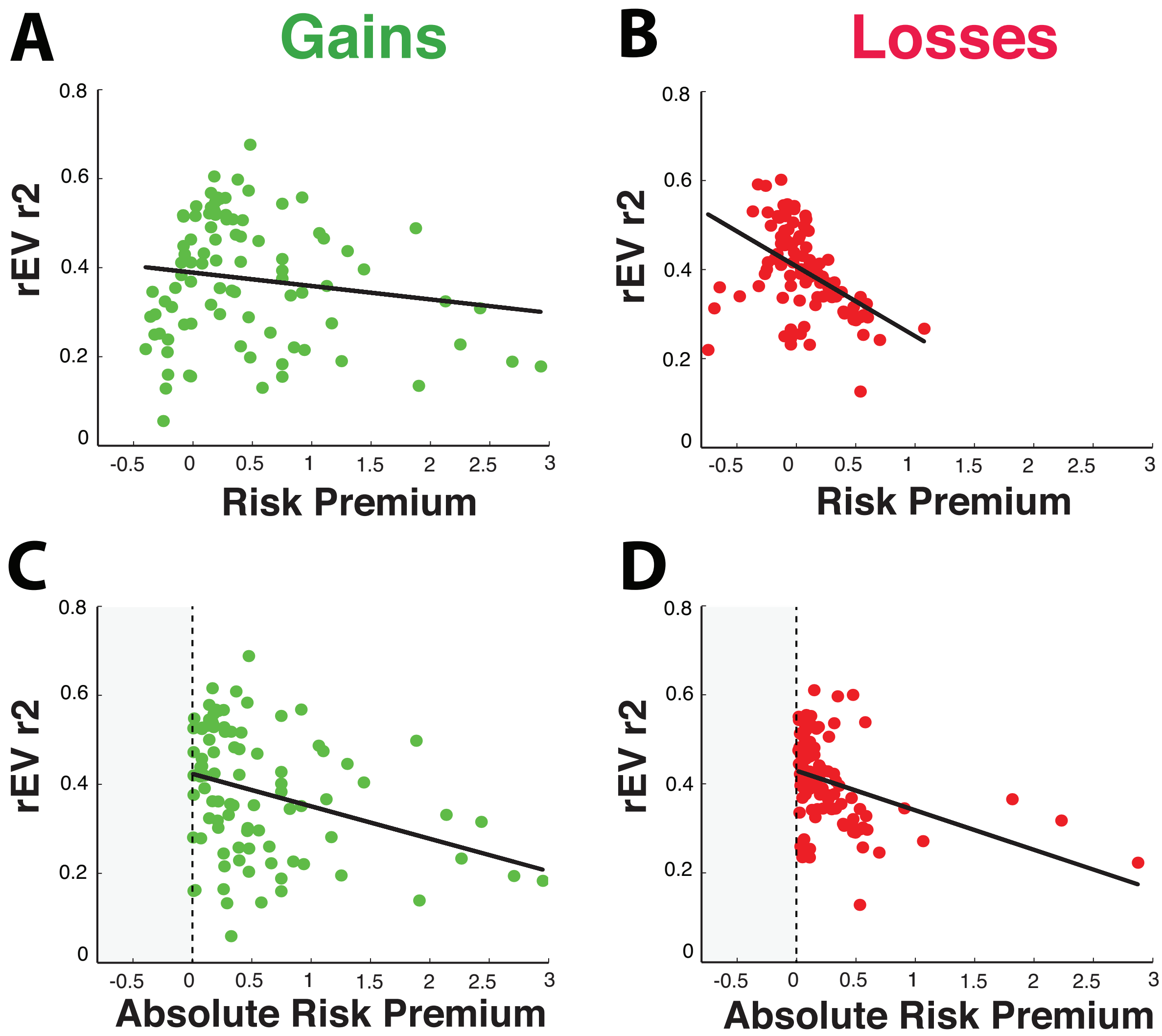

Figure 5.5. Relationship between individual risk premium and the degree to which participants relied upon the relative expected value (rEV) information in their choices in the (A) gains and (B) losses domains. A significant negative correlation is present for losses. **Relationship between individual deviation from neutral risk preference (absolute risk premium accounting for the non-linearity across zero) and reliance upon the rEV information in the (C) gains and (D) losses domains.** The vertical dashed line is drawn at risk neutrality (premium = 0), and the now-unattainable negative region is shaded gray. Following this transform, significant negative correlations are seen in both domains, indicating that as participants relied more heavily on the rEV information, their risk preferences became more risk neutral.

These results indicated that, in the losses domain participants with lower risk premium values made greater use of rEV information (maximizing) and relied less on pWIN information (satisficing). Interestingly, the zero-point for the risk premium metric reflects risk neutrality, so these results indicate that, for losses, the more an individual relied upon the maximizing information the more risk neutral their risk preferences were. Of note, this relationship is not a mathematical dependency (or by-product) of the task design or analyses (it is analytically possible for two people to have the same risk preference value yet employ different choice strategies).

This relationship between risk neutrality and maximizing strategies replicates a recent study using a blocked version of these tasks (gains trials first, then losses trials) (Kurnianingsih et al., 2015). Curiously, in that study, these effects were found only for older adults in the losses domain, while younger adults showed no such relationship. Potential explanations for the current expansion of this relationship to younger adults include sampling differences or an interaction with the interleaved gains and losses trials.

Relationship between absolute risk premium and choice strategies

We were curious about the domain-specificity of the relationship between risk premium and strategy, present for losses and absent for gains. We note that there is a wider distribution of risk preferences in the gains domain, with the majority of people risk averse but a significant number of people who are risk seeking. In addition, there is a non-linearity in the risk premium metric as you cross zero. To test whether this range of values was obscuring the same relationship as found in the losses domain, we sought to transform the data to reflect the distance of each participant from risk neutrality (regardless of sign). Standardly, this would be accomplished by taking the absolute value, however with the nonlinear relationship across zero for risk premium, the conversion of negative risk premium values to positive requires the formula [absolute premium value = 1/(premium value +1) – 1]. We performed this transformation for both the gains and losses domains, and re-ran the correlations between absolute risk premium and strategy. This resulted in significant negative correlations in both the gains ($r(89) = -.30$, $p = .004$) and losses ($r(97) = -.36$, $p < .001$) domains, with no significant difference across domains ($z = .43$, $p = .67$). The more each participant relied upon the maximizing rEV information, the more risk neutral their preferences were (Figure 5.5 C and D), across both gains and losses domains.

Relationship between numeracy and economic measures

We examined whether risk preferences and choice strategies were correlated with individual's numeracy ability. We found no significant correlations between risk premiums and numeracy score in the gains ($r(89) = .11$, $p = .28$) or losses domains ($r(97) = -.16$, $p = .11$), concurring with Tymula and colleagues (2013), but contrary to the recent findings by Schley and Peters (2014). We also examined the relationship between numeracy and the reliance on rEV information. We found a positive correlation between the amount of rEV information used and numeracy score in both the gains ($r(102) = .27$, $p = .005$) and losses domains ($r(102) = .23$, $p = .020$), indicating that individuals with better numeracy abilities make more use of the calculable rEV information.

Relationship between impulsivity and economic measures

We also examined whether risk preferences and choice strategies were correlated with individual's level of impulsivity. The average BIS-11 impulsiveness score across subjects was 63.62 (SD = 8.29). There was no significant correlations between risk premiums and impulsivity score in the gains ($r(89) = .04$, $p = .70$) or losses domains ($r(97) = -.03$, $p = .80$), agreeing with Huettel and colleagues (2006). For choice strategy, we also looked at the relationship between impulsivity and the reliance on trial information, rEV and pWIN. There was also no significant correlations between the amount of rEV information used and impulsivity score in the gains ($r(102) = -.13$, $p = .18$) or losses domain ($r(102) = -.05$, $p = .60$), nor were there any significant correlations between the amount of pWIN information used and impulsivity in the gains ($r(102) = .14$, $p = .15$) or losses domain ($r(102) = .05$, $p = .60$). These results indicate that the behavioral impulsivity measured by BIS-11 is independent from risk preference and choice strategy across both gains and losses.

Discussion

We investigated the differences between gains and losses decision making by examining the interrelationships between risk preferences and choice strategies across the gains and losses domains. On average, we find that participants were risk averse for gains and risk neutral for losses. In opposition to the reflection effect, individual risk preferences were uncorrelated across the gains and losses domains, though cross-domain risk preferences were still able to predict choices better than chance or random preference. Investigating the strategies that individuals employ, individuals showed greater reliance on the maximizing strategy in the losses domain than in the gains domain. Interestingly, we identified a correlation between risk preferences and choice strategies in the losses domain in which the more individuals relied upon the maximizing strategy the more risk neutral their risk preferences were.

Testing the sample reflection effect – average risk preferences in the gains and losses domains

First, we sought to replicate the classic pattern of risk preferences predicted by prospect theory (Kahneman & Tversky, 1979) – on average risk averse for gains and risk seeking for losses. In the gains domain, individuals were on average risk averse (based on risk premium and power function), concurring with prospect theory. In the losses domain, however, participants were on average risk neutral (risk premium metric) or weakly risk seeking (power function metric). These findings overall concur with the findings by Kahneman and Tversky (1979), indicating a sample-level reflection effect. We note, that this risk neutrality/weak risk seeking for losses still concurs with the original data that individuals are more willing to engage in gambles to prevent losses than to achieve gains – i.e., individuals are relatively more risk averse for gains than for losses.

Testing the individual reflection effect – are individual preferences correlated across domains?

The reflection effect suggests that the individuals who are most risk averse in gains will be the most risk seeking for losses – is this true? No. We do not find a significant relationship in the direction predicted by the reflection effect, using either risk preference metric (premium or power function). Our results indicate that risk preferences for gains, cannot predict individual risk preferences for losses, in concurrence with prior research (Cohen et al., 1987; Schoemaker, 1990; Laury & Holt, 2000; Kurnianingsih et al., 2015; Mullette-Gillman et al., 2015a; Mullette-Gillman et al., 2015b).

Interestingly, we find a non-significant correlation in the opposite direction of effect predicted by the reflection effect, using the risk premium metric (Table 5.1), in the same direction reported recently by Tymula and colleagues (2013). This suggests that the individuals who were most risk averse for gains were not the most risk seeking for losses (as predicted by the reflection effect), but remained the most risk averse in losses.

The reflection effect was originally identified in the comparison of average group risk behavior across gains and losses (Kahneman & Tversky, 1979). It is possible to reconcile the presence of a sample-level reflection effect, with our correlations that are opposite the predicted direction. Simply, these two results suggest that, for a significant number of individuals, the difference between gains and losses risk preferences is a shift in preferences (an additive component, as indicated by our regression analysis for the power function metric). In other words, for many people, those who are most risk averse for gains shift to become less risk averse, while those that are least risk averse shift to become less risk averse, risk neutral, or even risk seeking (depending on the degree of the shift).

Alternatively, while it is common to discuss risk preference as a unitary stable concept (such as a personality trait), there is also evidence that risk preferences may be independent across different domains. For example, evidence suggests independence of risk attitudes across domains such as investment, insurance, health, recreational, work, and social decisions (Hershey & Schoemaker, 1980; Weber et al., 2002). Interestingly, though we did not find any correlation between risk preferences across domains, we found that individual's cross-domain risk preferences did contain information that was able to facilitate prediction of choice behavior. Therefore, although risk preferences may be strongly context and domain dependent, an underlying general risk preference may moderate cross-domain factors.

One interesting question raised by these results is how to consider mixed gambles (those with both possible gains and losses components). It is unclear whether gains and losses risk preferences would be predictive of behavior over mixed-gamble.

Difference in choice strategies between the gains and losses domains

We examined whether the trial information individuals rely upon to make their choices differs across the gains and losses domains. While both domains featured greater reliance on the rEV information over the pWIN, there was even greater reliance on rEV information in the losses domain than in the gains domain. There is inherently no difference in the difficulty of calculations across the gains and losses domains, suggesting this result must be due to enhanced motivation in the losses domain; that participants were more willing to engage in the effortful rEV calculations to avoid possible losses than to reach possible gains. This concurs with recent studies that have found that incentives framed as losses result in higher work productivity compared to incentives framed as gains (Fryer et al., 2012; Hossain & List, 2012).

Relationship between risk preference and choice strategy

In both the gains and losses domains, we found a negative correlation between distance from risk neutrality and the degree to which participants used the rEV information (the maximizing strategy in our task). Importantly, this relationship is not due to a mathematical dependency in the task or analyses, but is the result of the behavior of the participants (in other words, in our task/analyses it is possible for participants to have any pairing of risk preferences with any strategy value).

Risk neutral preferences suggest the absence of value modulation due to uncertainty – that participants were unbiased by uncertainty. As risk neutrality is the point where utility maximization converges with value maximization, this relationship indicates that those people who relied more on the use of rEV information, used the information not only to maximize their utility but were simultaneously maximizing the expected value of the outcomes.

In our task, the maximizing strategy requires deliberative cognitive processing, and we find a relationship between higher reliance on such deliberative reasoning and risk neutral preferences. In contrast, higher reliance on automatic cognitive processes bias preferences away from neutrality. These results concur with suggestions that risk may modulate decision making away from neutrality due to inclusion of affective responses (e.g. anticipated fear of loss) (Loewenstein et al., 2001). Such differential influences of cognitive and affective processes is described by dual cognitive theory, in which there is a competition between slow-deliberative and automatic-effortless processing during the decision making process (Kahneman & Frederick, 2002; Evans, 2003). As a result, as individuals increased reliance on the maximizing strategy, this would have competitively reduced inclusion of affective biases, resulting in more neutral risk preferences.

An interesting possibility is that this relationship between risk preferences and choice strategy may provide a potential explanation as to why risk preferences appear to vary across different contexts (such as financial, health, and social domains; Weber et al., 2002). If risk preferences are driven by the choice strategy, and if the available types or quality of information varies across contexts, then a stable underlying risk preference could be differentially expressed across different contexts/domains. Similar choice strategies may reflect the same underlying cognitive processing modulating the risk preferences used to govern choices made. As such, varying risk preferences across contexts may be due to necessarily differential strategies due to domain-specific information.

Explanation for framing effect?

These findings offer a potential explanation for the framing effect. Standardly, studies examining the framing effect observe a shift in risk preferences between the presented relative gains and relative losses, with participants more willing to accept gambles in which they can avoid a possible loss (for review, see Kühberger, 1998; Levin et al., 1998). We show that this shift in risk preference is not due to the reflection effect, which would have suggested that the same cognitive/neural processes are engaged in either domain. Rather, we see independence between risk preferences across the gains and losses domains, which suggests that different cognitive/neural mechanisms are engaged when prospects are framed as gains and losses and that an individual's choices in one domain cannot predict choices in the other domain. In other words, while the relative gain option and the relative loss option are mathematically equivalent there may be significant differences in the cognitive/neural systems that are engaged to process these options. If so, a simple transformation of the available options (such as altering the values from absolute to relative a mid-value) could result in dramatically different decisions as different cognitive processes / neural substrates are engaged.

Conclusions

In this study, we found multiple indicators of independence and differentiation in gains and losses decision making. For risk preferences, utilizing two different preference metrics, we replicated the differentiation of average preferences for gains and losses, with risk averse for gains and risk neutral/seeking for losses. However, moving to individual participants, we were unable to show the interrelationship of risk preferences predicted by prospect theory and the reflection effect. Examining the strategies that participants employed to make their choices, across domains, individuals placed greater reliance on the effortful maximizing strategy, and the more they relied on this choice strategy the more their preferences were neutral. However, we did not show pure independence across gains and losses decision making. Cross-domain risk preferences still had predictive information about choices, even though we found not only non-significant but also opposite-signed correlations from that predicted by prospect theory's reflection effect.

Taken together, these findings suggest that gains and losses decision making are the result of both separable and overlapping cognitive/neural mechanisms. The separability is suggested by the independence of risk preferences across domains – even in intermixed gains and losses trials preferences across domains were uncorrelated. The overlap is suggested by the maintained predictive power of cross-domain risk preferences and the cross-domain relationship between risk preferences and strategies.

A possible explanation for such simultaneous separability and overlap is in the encoding and interactions of the valuative and executive processes. Although gains and losses are trivially related mathematically, and both provide motivation for decision making, they are the result of extremely different evolutionary pressures and the cognitive processes / neural mechanisms will reflect such convergence and divergence. Separabilities in behavior will arise to the degree there is differential/divergent neural encoding of the valuative/affective signals for gains and losses (Bartra et al., 2013; Pessiglione & Delgado, 2015). Overlapping behavior will arise from engagement of shared/convergent non-valuative processes, such as executive processes related to working memory and contingency processing (Miller & Cohen, 2001; Mullette-Gillman & Huettel, 2009). As these shared executive and differential valuative processes interact (Mullette-Gillman et al., 2011), they will result in aspects of behavior that exhibit both convergence and divergence between the gains and losses domains.

Chapter 6: Neural mechanisms of the transformation from objective value to subjective utility[9,10]

This chapter reports about an fMRI study where we sought to identify neural regions that were related to the degree and direction of individual's value modulation. In the previous four chapters, we found consistent patterns in risk preferences across all our behavioral studies. Importantly, we were able to quantify individuals' risk preference and demonstrate that individuals were making their choices based on their risk preference. As risk preference measures the degree to which individuals are modulating value, this opens up exploration of how and where in the brain this value modulation is taking place. Additionally, we found no relationship between gains and losses risk preferences – preferences in one domain cannot predict preferences in the other. We leveraged the independences of gains and losses risk preferences to perform a within-study replication across almost perfectly matched trials (only the signs between gains and losses were different).

Abstract

When deciding, we aim to choose the "best" possible outcome. This is not just selecting the most numerous or physically largest, as options are translated from objective value (count) to subjective value (worth or utility). We localized the neural instantiation of the value-to-utility transformation to

[9] This paper has been previously published: Kurnianingsih, Y.A. & Mullette-Gillman, O.A. (2015). *Neural mechanisms of the transformation from objective value to subjective utility*. *Front. Neurosci.* 10:507. doi: 10.3389/fnins.2016.00507

[10] Contributions: OAMG conceived the experiment. OAMG and YA designed the experiment; YA collected the data under the supervision of OAMG; YA and OAMG analyzed the data and wrote the manuscript.

the dorsal anterior midcingulate cortex (daMCC), with independent replication. The daMCC encodes the context-specific information necessary to convert from count to worth. For a given value, daMCC activation corresponds to diminished subjective valuation, deactivation to enhanced subjective valuation, and non-modulated activation with non-modulated subjective valuation. This encoding is not simply a representation of utility, as the relationship of brain activation to value is dependent on individual preference, with both positive and negative slopes across the population depending on whether each individual's preference results in enhancement or diminishment of the valuation. Further, functional connectivity analyses identified brain regions (positive connectivity with the inferior frontal gyrus and negative connectivity with the nucleus accumbens) through which contextual information may be integrated into the daMCC and allow for outputs to modulate valuation signals. These results identify the neural locus of the value-to-utility transformation, and provide a specific computational function for the daMCC in the production of subjective valuation through the integration of value, context, and preferences.

Introduction

In decision making, we strive to select the best option, but this is not simply the selection of the physically largest option or the option with the most numerous items. We determine the subjective valuation of each option (utility or worth) by integrating context and history. For instance, whereas a hungry person has a high subjective value for food, a satiated person may find the same food neutral or aversive. In monetary decision making, varied subjective valuation is clearly demonstrated in individual responses to risky gambles (uncertain outcomes), in that individuals may be willing to pay quite different prices for a lottery ticket with an expected value of $10 (50% chances of $20 or $0). While most individuals place their subjective valuation below the expected value (risk aversion), others enhance the subjective value of the ticket (risk seeking). The degree and direction of their subjective valuation describes the specific value-to-utility transformation each participant is performing.

As subjective valuation is the basis of choices, it is essential to understand the mechanism behind the value-to-utility transformation. Many prior studies have investigated how value is encoded in the brain. Meta-analyses of fMRI studies examining neural correlates of value have found that the ventromedial prefrontal cortex (vmPFC) encodes value signal (Clithero & Rangel 2013; Bartra et al., 2013). Although consistently found across tasks and modalities, the majority of studies focus only on the reward/gains. While a few studies investigating losses have also reported value signals in the vmPFC, we note that those studies used either mixed gambles (Tom et al.,

2007) or avoidance of aversive stimuli (Plassman et al., 2010; Litt et al., 2011) which may potentially be interpreted positively as relief from negative stimuli (Kim, Shimojo & O'Doherty, 2006), causing the possibility of interaction with the reward system in the losses. As such, it has not been clearly demonstrated whether there is a general valuation system encompassing both gains and losses valuation or whether there are significant differences in the neural processing of valuation across gains and losses.

In order to determine utility, the value under consideration and individual's preference based on the specific context must be integrated. Several lines of evidence have suggested the involvement of dorsomedial prefrontal cortex (dmPFC) in integrating information during decision making (Rushworth & Behren, 2008; Venkatraman et al., 2009; Xue et al., 2009, Hare et al., 2011) and also in action-based value comparison (Wunderlich et al., 2009; Rangel & Hare, 2010; see Walton et al., 2007 for review). Based on these previous findings, we posit the dmPFC as a potential locus of the executive modulation of value processing. In addition to the dmPFC, there have been suggestions that value may be modulated in other areas of the brain, for example, in the inferior parietal lobule (IPL) during empathic decision making (Janowski, Camerer & Rangel, 2011) and in the dorsal lateral prefrontal cortex (dlPFC) for decision making involving self control (Hare, Camerer & Rangel, 2009).

In this study, we identified the brain region that encodes the information necessary to perform the value-to-utility transformation. To do so, we employed a precise computational model that leveraged the idiosyncratic subjective valuation of each participant across 9 levels of objective value –

identifying a brain region that not just encodes a linear signal of value, but whose slope (from positive to negative) is dependent upon the preferences of each individual.

To ensure the viability of our computational model, we first replicated prior studies (Bartra et al., 2013; Clithero & Rangel, 2014) by localizing valuation signals to the vmPFC. These analyses identify brain regions whose activation is correlated with the presented values, with a common slope across individuals. Critically, we then expanded upon these analyses by covarying the value regressor by each individual's behaviorally derived risk preferences – to identify regions that encode a linear value signal whose slope varies across individuals based upon their specific value-to-utility transformation. Our final aim was to identify the network of brain regions involved in the value-to-utility transformation, through functional connectivity analyses.

Thirty participants engaged in a two-alternative forced choice risky monetary decision task (Kurnianingsih & Mullette-Gillman, 2015) while undergoing fMRI scanning. Participants performed 270 trials choosing between a certain and a risky option, with half of the trials in the gains domain and half in the losses domain (Figure 6.1). For gains, the trial matrix was made up of five different values of the certain option ($V_{Certain}$){\$3, \$4, \$5, \$6, \$7}, with the gamble option constructed from three probabilities of winning (pWIN){25%, 50%, 75%} and nine relative expected values between the certain and gamble options ($rEV = EV_{Gamble} / V_{Certain}$){.25, .50, .66, .80, 1.0, 1.25, 1.50, 2.0, 4.0}. Losses trials were constructed from the same matrix, with negatively mirrored certain values ($V_{certain}$). An additional 74 trials consisted of choices between two certain options (see Materials and Methods).

The trials were divided equally into four runs, with trial order randomized independently for each participant. Choices were incentive compatible, with resolution of one randomly selected trial from each domain for each run. This study features within-study replication – neuroimaging analyses were first performed on gains trials and then replicated within losses trials, allowing for almost perfectly matched and intermixed tasks – differing only by sign and individual preferences.

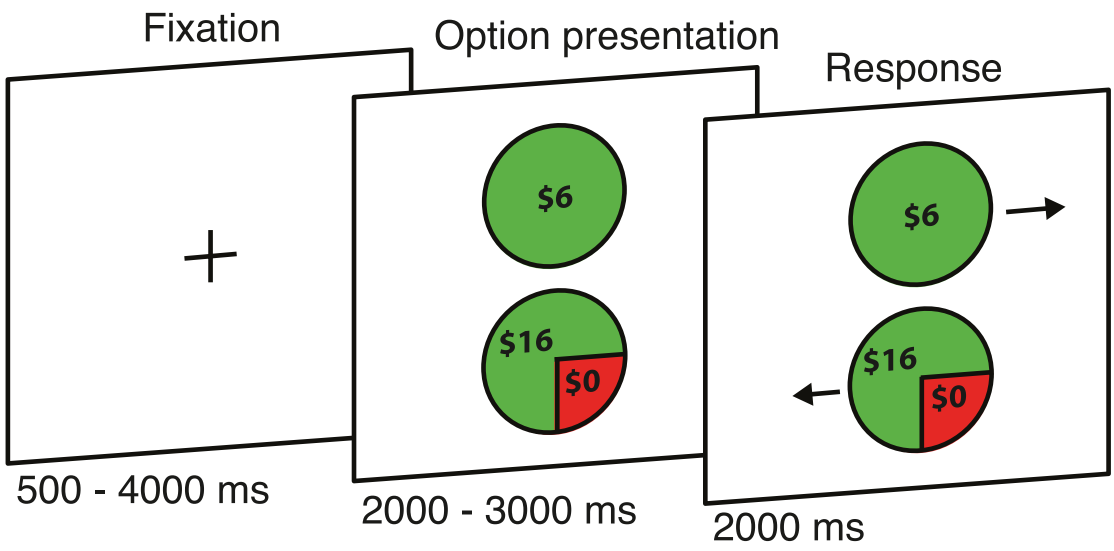

Figure 6.1. Example trial of the risky monetary decision task. Each trial begins with the presentation of two options, followed by an arrow appearing at the side of each option (position randomly interchanged) to indicate which button should be pressed to select that option.

Materials and Methods

Participants

Thirty healthy subjects (15 males, *mean* ± *SD* age = 22 ± 1.74 years old) were recruited from the National University of Singapore as participants in this study. They were all right-handed with no history of neurological or psychiatric disorders. Participants provided written informed consent under a protocol approved by the National University of Singapore Institutional Review Board. fMRI scanning was conducted in the Duke-NUS Graduate Medical School, Singapore.

Study Procedure

Participants participated in two sessions: a behavioral session followed by an fMRI session (8 to 152 days in between). During the behavioral session participants performed the risky monetary decision task using a computer outside the scanner (results published in Kurnianingsih & Mullette-Gillman (2015)). Participants whose choices did not rely on confounding behavioral choice patterns (such as always choosing the risky or certain option) were invited to return for the fMRI session. During the fMRI session, participants performed the risky monetary decision task inside the MRI scanner.

Risky Monetary Decision Task. We used a modified version of a risky monetary decision task (Kurnianingsih & Mullette-Gillman, 2015), with an equal number of trials evaluating the gains and losses domains, randomly intermixed. On each trial, participants chose between a gamble and a certain option (270 trials) or between two certain options (74 trials). For certain vs. certain trials in the gains domain, the trial matrix was constructed from five different certain values for the first option ($V_{Certain1}$){\$3, \$4, \$5, \$6, \$7}, and the values of the second option were calculated based on the combination of $V_{Certain1}$ and rEV ($V_{Certain2} = rEV \times V_{Certain1}$), with nine different relative expected values (rEV){.25, .50, .66, .80, 1.0, 1.25, 1.50, 2.0, 4.0}. Note, that this process results in a small number of duplicate trials, which were not included. The losses trials were similar to the gains trials, save for shifting the valence of the values offered into negative values. Behavioral data collection and analyses were achieved using Matlab R2010B (Mathworks, Natick, MA) with Psychtoolbox (www.psychtoolbox.org) (Brainard, 1997) for trial presentation. No trials were resolved before the end of the experimental session, to prevent feedback from altering subsequent behavior (learning). At the beginning of the session, participants were informed that at the end of the session their payment would be determined from resolution of one gains trial and one losses trial randomly selected from each run (four actual runs and one practice run, for a total of 10 trials).

fMRI task design. Each participant underwent four runs; each run consisted of 43 gains trials and 43 losses trials, lasting for 9 minutes and 22 seconds. Each trial began with the presentation of the two options (2000 ms–3000 ms) followed by arrows appearing at the left or right side of each option (2000 ms). Participants had 2000 ms to respond, by pressing the key on the button box that corresponded to the direction of the arrow presented beside their preferred option (position randomly interchanged). After a response was made, the screen presentation was immediately replaced by a fixation cross for the remainder of the 2000 ms and then continued during the inter-trial intervals (500 ms–5500 ms). In other words, quick responses do not reduce the duration of the run but increase the baseline time (improving the fMRI signal to noise ratio). All trials and time intervals within each block were fully randomized for each participant.

To ensure that participants were incentivized to not miss trials, they were informed that if a missed trial was selected for resolution towards their payment, an option would be randomly selected and an additional penalty of -$2 applied. Any such missed trials were excluded from analyses. On average, participants missed .18 gains trials (*SD* = .52, with a range of 0 to 3, *mean* ± *SD* = .43% ± 1.21%) and .41 losses trials (*SD* = .87, with a range of 0 to 5, *mean* ± *SD* = .96% ± 2.02%). Missed trials were excluded from analyses.

We excluded one run of one participant from fMRI analyses due to a technical problem during data acquisition.

Practice task. Before entering the MRI scanner, participants were given a set of computerized practice trials. The practice task consisted of 60 risky vs. certain trials, constructed from two possible rEV{.33, 3.0} and three possible probabilities of winning (pWIN){25%, 50%, 75%} in both the gains and losses domains. Trials were presented as they would be inside the MRI scanner, but were not included in behavioral analyses.

Behavioral Analysis. ***Quantifying risk preferences.*** We quantified risk preferences separately for the gains and losses domains, by using these power functions (Tymula et al., 2013; Kurnianingsih & Mullette-Gillman, 2015):

For gains (if V > 0): $SV = pWIN \times V^{\alpha}$

For losses (if V < 0): $SV = -(1-pWIN) \times (-V)^{\alpha}$

where SV is the subjective value (utility) of the gamble, pWIN is the probability of receiving the better outcome of the option (assuming linear probability weighting), V is the objective value of the option (which is the nominal value that was presented), and α is the degree of the power function curvature that represents the degree each participant modulates the values of the options. In the gains domain, an α < 1 indicates value diminishment (SV < V, risk averse), an α = 1 indicates the absence of value modulation (SV = V, risk neutral), and an α > 1 indicates value enhancement (SV > V, risk seeking). Due to the negative signs in the losses domain, the opposite applies. In the losses domain, an α < 1 indicates value enhancement (risk seeking), an α = 1 still indicates the absence of value modulation (risk neutral), and an α > 1 indicates value diminishment (risk averse).

In order to determine participant's risk preference, participant's choice data were fitted using maximum likelihood with a probability choice function:

Probability of choosing the gamble option = $\frac{1}{1+e^{-(SV_G - SV_C)}}$

Where SV_c is the subjective value of the certain option and SV_G is the subjective value of the gamble option.

MRI Data Acquisition. MR images were acquired on a 3T Siemens Tim Trio (Siemens, Erlangen, Germany). Visual stimuli were back-projected onto a screen positioned behind the scanner bore (Epsom EMP1715, 800×600 pixels, 60 Hz). Four runs of 283 volumes each were acquired using a gradient echo-planar imaging (EPI) sequence with the following parameters: repetition time (TR) = 2000 ms; echo time = 30 ms; flip angle = 90 degrees; field-of-view (FoV) = 192×192 mm; matrix size = 64 × 64 with resolution of 3 mm × 3 mm). Each volume consisted of 36 slices collected in an interleaved ascending manner. The slices were aligned to the anterior commissure-posterior commisure (AC-PC) plane. We also obtained a T1-weighted coplanar image and a high-resolution T1-weighted anatomical volume (1 mm × 1 mm) acquired using a 3D-MPRAGE sequence to assist with image co-registration.

Image preprocessing and statistical analysis. Image processing and statistical analysis were conducted using FSL Version 5.0.2.2 FEAT Version 6.0 (Brainard, 1997) and MATLAB R2010B (Mathworks, Natick, MA), with visualization of neural results using MRIcron (Rorden et al., 2007) and MRIcroGL (http://www.cabiatl.com/mricrogl/). A total of ten volumes were discarded to ensure sufficient time for the scanner signal to reach equilibrium. Brain extraction of the functional and anatomical images was performed with FSL's Brain Extraction Tool (BET) (Smith, 2002). Functional runs were spatially smoothed using a 5mm full-width-half-maximum Gaussian kernel, filtered in the temporal domain using a high pass filter cutoff of 30s and motion corrected using MCFLIRT (Jenkinson et al., 2002). Translation movements were less than 1 voxel for all runs of all subjects. Functional images were normalized using FLIRT (Jenkinson & Smith, 2001; Jenkinson, 2002), by estimating the transform from individuals' T1-weighted coplanar (6 degree-of-freedoms) and high-resolution T1-weighted anatomical image (7 degree-of-freedoms); the resulting data were then aligned into MNI standard space (12 degree-of-freedoms). All reported neuroimaging main effects and contrasts unless specified utilize a height threshold of $z > 2.3$ and a standard cluster probability of $p < .05$.

General Linear Model (GLM). *GLM1.* The base GLM model had five predictors, each convolved using a double gamma hemodynamic response function. This model is a basic 2×2 design (risky/certain × gains/losses), with box-car encoding the decision phase (option onset to button press) of each of the four types of trials (#1 gains trials with risky vs. certain options regressor, #2 losses trials with risky vs. certain options regressor, #3 gains trials with certain vs. certain options regressor, and #4 losses trials with certain vs. certain options regressor), and including a nuisance regressor for button presses (regressor #5, 500ms starting at press). For main effects of trial types, and contrasts between, see Tables 6.2 and 6.3.

GLM2 a, b and c. These three additional models investigated value signal coding across trials in varied theoretical formulations. The [Value] formulations examined were rEV (relative expected value; expected value of the gamble divided by the value of the certain option), CV (chosen value; the expected value of the chosen option), and rCV (relative chosen value; the expected value of the chosen option divided by the expected value of the unchosen option). Separate GLMs were performed to examine each of [Value] formulations (*GLM2 a, b* and *c*, respectively), as they are correlated across trials (Table 6.1).

Table 6.1. Median correlations between parametric regressors across runs

Median (SD)		RC Trials			CC Trials	
		rEV	rCV	CV	rEV	rCV
Gains RC Trials	rCV	.357 (.234)				
	CV	.831 (.138)	.537 (.085)			
	pWIN	.003 (.105)	.083 (.120)	.033 (.152)		
Gains CC Trials	rCV				1.000 (.035)	
	CV				.831 (.138)	.513 (.117)
Losses RC Trials	rCV	-.348 (.288)				
	CV	-.413 (.121)	-.398 (.198)			
	pWIN	-.024 (.099)	-.169 (.146)	.082 (.109)		
Losses CC Trials	rCV				.956 (.256)	
	CV				.249 (.201)	-.259 (.219)

*Relative expected value in the certain vs. certain trials is calculated based on the ratio of the larger certain value to the smaller certain value.
Abbreviations: RC, risky vs. certain; CC, certain vs. certain; rEV, relative expected value; rCV, relative chosen value; CV, chosen value; pWIN, probability of winning.

Each of the *GLM2* (*a*, *b*, and *c*) models featured the addition of six additional predictors: #6 parametric regressor of [Value] in gains trials with risky vs. certain options, #7 parametric regressor of [Value] in losses trials with risky vs. certain options, #8 parametric regressor of pWIN in gains trials with risky vs. certain options, #9 parametric regressor of pWIN in losses trials with risky vs. certain options, #10 parametric regressor of [Value] in gains trials with certain vs. certain options, and #11 parametric regressor of [Value] in losses trials with certain vs. certain options. Each of these regressors (#6 to

#11) encoded the entire decision phase, from onset of option presentation to the button press response, and were convolved with a double gamma hemodynamic response function. The pWIN regressors were both orthogonalized with respect to the risky vs. certain options [Value] regressor within their respective domains.

To identify the neural encoding of the value-to-utility transformation, covariate analyses were performed separately for the gains and losses domains by including each individual's risk preference values for each domain as a between-subject covariate into the GLM model. Beta values were extracted from a daMCC ROI (Figure 6.3C and 6.4C), constructed through a conjunction analysis of the separate gains and losses covariate analyses.

GLM3. This categorical model allows for the extraction of the actual functional neural encoding of the rEV value signal. This model consisted of *GLM1* plus 18 additional categorical regressors. The risky vs. certain trials were grouped according to their rEV (2 domains × 9 rEVs) and each rEV value was represented by a boxcar task regressor encoding the entire decision phase, from option presentation to response button press, and convolved with a double gamma hemodynamic response function.

Psychophysiological interaction (PPI) analysis. This analysis was performed to examine brain regions that have task-related functional connectivity with the daMCC during the decision period. We utilized the daMCC ROI produced as the conjunction of the voxels found to contain the value-to-utility transformation information across both the gains and losses domains. For each individual, an average time series of the voxels within the daMCC seed ROI was computed from the voxels for each trial type. A GLM model was estimated by adding in eight additional regressors to *GLM1* model (two additional regressors for each trial type). These additional regressors were the time course of the seed ROI averaged across the ROI voxels, and the interaction between the time course regressor and boxcar trial type regressor for each trial type.

Results

Contrasting decision types within and across gains and losses.

We determined gross differences in brain activations between the trials in which participants chose between risky and certain options and those trials in which they chose between two certain options, examined separately within the gains and losses domains (Table 6.2). We also identified differences in the brain activations between gains and losses for each trial type (Table 6.3).

Table 6.2. GLM1: Brain areas exhibiting significant differences in activation across trial types within each domain.

		# voxels	Region	Hemisphere	Peak Coordinates x	y	z	z-stat
Gains	RC > CC	13817	Paracingulate Gyrus (*dmPFC)	L	-2	34	32	5.75
				mid	0	24	46	5.65
			Inferior Frontal Gyrus	L	-50	18	28	5.44
		26578	Lateral Occipital Cortex	L	-38	-88	8	6.99
				L	-34	-86	8	6.82
				L	-34	-82	-14	6.74
		2461	Posterior Cingulate Gyrus	L	-2	-24	28	5.21
				mid	6	-30	26	4.58
			Caudate	R	14	20	-4	4.16
	CC > RC	1044	Frontal Medial Cortex (*vmPFC)	L	-2	48	-20	4.13
				L	-6	40	-22	3.73
			Frontal Pole	R	4	60	6	3.53
		2422	Supramarginal Gyrus	R	62	-36	28	5.85
				R	62	-44	34	5.35
				R	62	-26	22	5.12
		1865	Supramarginal Gyrus	L	-64	-34	26	5.02
				L	-66	-26	26	4.81
				L	-64	-42	42	4.42
		809	Postcentral Gyrus	R	12	-38	50	4.06
			Anterior Cingulate Gyrus	mid	0	-14	40	3.99
			Posterior Cingulate Gyrus	R	10	-28	40	3.67
Losses	RC > CC	23397	Lateral Occipital Cortex	L	-34	-90	12	6.39
				R	28	-64	52	5.84
			Middle Temporal Gyrus	R	40	-58	46	6.09
		17405	Inferior Frontal Gyrus	L	-4	26	38	6.53
			Posterior Cingulate Gyrus	L	-2	20	44	6.12
			Frontal Pole	L	-40	48	0	5.66
		4092	Lateral Ventricle	R	6	0	22	4.56
			Thalamus	L	-20	-30	2	4.41
				R	16	-18	0	4.15
	CC > RC	1338	Supramarginal Gyrus	R	66	-36	32	4.99

				R	64	-42	36	4.69
				R	66	-44	28	4.65
		1191	Frontal Medial Cortex (*vmPFC)	L	-10	50	-10	4.46
			Cingulate Gyrus	L	4	36	-8	4.28
			Subcallosal Cortex	L	-4	24	-16	4.1
		969	Supramarginal Gyrus	L	-66	-28	26	4.57
				L	-60	-28	24	4.17
				L	-62	-40	36	4.07

Abbreviations: RC, risky vs. certain; CC, certain vs. certain; vmPFC, ventromedial prefrontal cortex; dmPFC, dorsomedial prefrontal cortex.
Regions are labeled based upon their Harvard-Oxford Atlas designations, with parenthetical inclusion of labels from text.
The coordinates for the three peak activations are provided for each cluster, in MNI space (in mm).

Table 6.3. GLM1: Brain areas exhibiting significant difference in activation across the gains and losses domains, within each trial type.

		# voxels	Region	Hemisphere	Peak Coordinates *x*	*y*	*z*	*z-stat*
CC	Losses > Gains	443	Caudate	R	16	26	-8	4.04
				R	22	28	4	3.5
				R	4	16	-4	3.47
		449	Inferior Frontal Gyrus	R	48	10	22	3.41
				R	30	14	20	3.32
				R	42	0	20	3.28
		4867	Lateral Occipital Cortex	L	-42	-90	-8	6.27
			Occipital Pole	L	-34	-94	2	5.42
				L	-20	-94	-14	5.4
		5095	Occipital Pole	R	34	-92	-4	5.55
			Lateral Occipital Cortex	R	32	-88	-14	5.21
			Occipital Fusiform Gyrus	R	38	-72	-16	5.06
RC	Gains > Losses	435	Frontal Medial Cortex (*vmPFC)	mid	0	42	-14	3.58
				R	8	40	-22	3.37
			Frontal Pole	R	12	40	-20	3.34
RC	Losses > Gains	11059	Inferior Frontal Gyrus	R	44	12	26	5.6
				L	-40	10	22	4.79
			Paracingulate Gyrus (*dmPFC)	mid	0	16	46	4.6
		890	Thalamus	R	8	-14	8	3.83
				R	18	-10	18	3.5
				L	-20	-30	8	3.25
		17479	Occipital Pole	L	-26	-98	-8	5.55
			Occipital Fusiform Gyrus	R	30	-86	-10	5.51
			Hippocampus	L	-34	-34	-90	5

Abbreviations: RC, risky vs. certain; CC, certain vs. certain; vmPFC, ventromedial prefrontal cortex; dmPFC, dorsomedial prefrontal cortex.
Regions are labeled based upon their Harvard-Oxford Atlas designations, with parenthetical inclusion of labels from text.
The coordinates for the three peak activations are provided for each cluster, in MNI space (in mm).

Identifying the neural encoding of value signal for gains.

Numerous studies have shown that activation within the vmPFC is parametrically modulated by the value presented on each trial (Bartra et al., 2013; Clithero & Rangel, 2014). While this result is robust across numerous studies, it is still unclear how value is specifically represented in the brain. As we sought to utilize a value signal as a component of our localization of the value-to-utilty information, we first tested three different ways of formulating the value on each trial, in order to identify the one most robustly represented in the vmPFC during decision making. These three formulations were: 1) the ratio of the expected value of the gamble to the value of the certain option ($EV_{gamble}/V_{certain}$, which we will refer to as rEV); 2) the expected value of the chosen option (which we will refer to as CV); and 3) the ratio of the expected value of the chosen option to the expected value of the unchosen option ($EV_{chosen}/EV_{unchosen}$, which we will refer to as rCV). Each of these value formulations was tested with an independent general linear model (GLM), examining the whole-brain encoding of parametric value signals within the trials in which participants chose between risky and certain options in the gains domain (Figure 6.2; Table 6.4; utilizing *GLM2*).

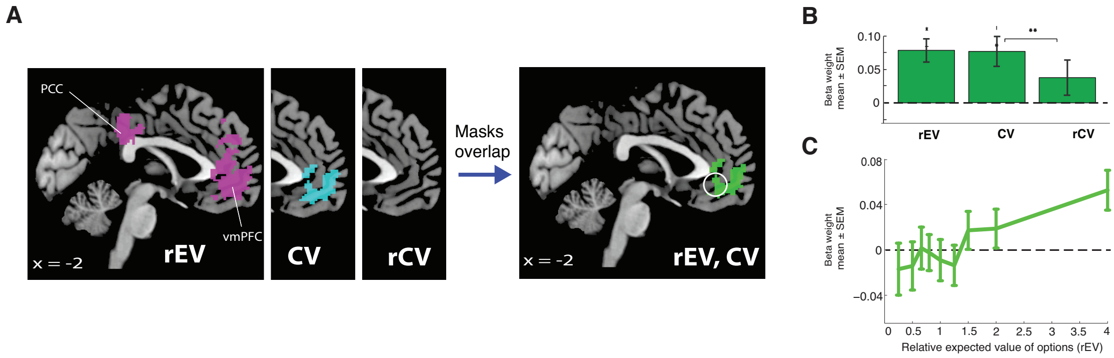

Figure 6.2. Neural encoding of value signals for gains. (A) Whole brain analyses localizing value signals with three different value regressors (relative expected value, rEV; chosen value, CV; relative chosen value, rCV). The white circle indicates the unbiased 10 mm spherical vmPFC ROI (x = -2, y = 40, z = -8). (B) vmPFC ROI analyses demonstrate the strength of the encoding for each of the three tested formulations of trial value (*: significantly different from 0; **: significantly different from each other). (C) Extracted functional relationship between vmPFC activation and each gain rEV category, extracted from the vmPFC ROI.

Table 6.4. GLM2: Brain areas exhibiting significant encoding of parametric value signals in the gains domain.

	# voxels	Region	Hemisphere	Peak Coordinates *x*	*y*	*z*	*z-stat*
rEV	2474	Frontal Medial Cortex (*vmPFC)	R	4	50	-8	3.97
			R	6	40	-14	3.91
		Paracingulate Gyrus	R	4	44	-8	3.91
	533	Posterior Cingulate Gyrus (*PCC)	R	6	-30	30	3.65
			R	4	-34	36	3.63
			L	-2	-36	44	3.62
	473	Middle Temporal Gyrus	R	58	-56	-6	3.68
			R	62	-54	-6	3.66
		Inferior Temporal Gyrus	R	52	-50	-14	3.46
	528	Lateral Occipital Cortex	R	24	-82	50	3.49
			R	26	-60	42	3.29
			R	32	-66	46	3.28
	2381	Occipital Pole	L	-20	-102	0	4.29
		Lateral Occipital Cortex	L	-40	-90	16	3.84
			L	-34	-86	10	3.83
CV	1107	Frontal Medial Cortex (*vmPFC)	R	6	40	-14	4
			R	2	44	-8	3.83
			L	-10	38	-12	3.47
	1128	Occipital Pole	L	-20	-102	0	3.73
			L	-26	-98	6	3.4
		Lateral Occipital Cortex	L	-22	-76	52	3.39

Abbreviations: rEV, relative expected value; CV, chosen value; vmPFC, ventromedial prefrontal cortex; PCC, posterior cingulate cortex.
Regions are labeled based upon their Harvard-Oxford Atlas designations, with parenthetical inclusion of labels from text.
The coordinates for the three peak activations are provided for each cluster, in MNI space (in mm).

We found clear indications of the encoding of parametric value signals within the vmPFC for both the rEV and CV value formulations, with large overlap between the two models (Figure 6.2A). We compared these models by extracting the beta values for each parametric value regressor from an unbiased 10mm spherical vmPFC region-of-interest (ROI) (x = -2, y = 40, z = -8), centered on the peak coordinate of parametric value signals reported in a meta-analysis study by Bartra and colleagues (2015) (Figure 6.2B). The strengths of the representations of the rEV and CV value formulations were not significantly different from one another (t_{29} = .15, p = .88). The rCV formulation resulted in no significant voxels at the whole-brain level, and the ROI analyses confirmed that the strength of the encoding was not significantly greater than zero (t_{29} = 1.46, p = .15) and was significantly less than the rEV and CV formulations (rEV t_{29} = 2.03, p = .051; CV t_{29} < 2.90, p = .007).

Given the design of our task, with 15 trials for each of the 9 levels of the rEV formulation, we were able to visualize the actual neural encoding of the rEV formulation within the vmPFC ROI by extracting the beta values for each level of the rEV formulation (utilizing *GLM3*). The encoding of gains value signals in the vmPFC demonstrated a clear positive relationship between value and brain activation (Figure 6.2C). As the rEV and CV formulations were equally well represented, we chose to focus further analyses on the rEV factor. Post-hoc analyses (below) demonstrate the congruence of results across both the rEV and CV formulations.

Identifying the neural encoding of the value-to-utility transformation, in gains

The purpose of this project was to examine the neural mechanisms of the value-to-utility transformation. To do so requires quantifying the value-to-utility transformation that each participant is engaging in. We determined the value modulation of each participant based on their risk preference as expressed by their choices, modeled as the degree of curvature (α) of their individual utility function, a power function (Tymula et al., 2013). In the gains domain, participants were on average risk averse (utility less than value, *mean* $\pm SD\ \alpha = .84 \pm .21$), with a wide range of preference values (Figure 6.3A).

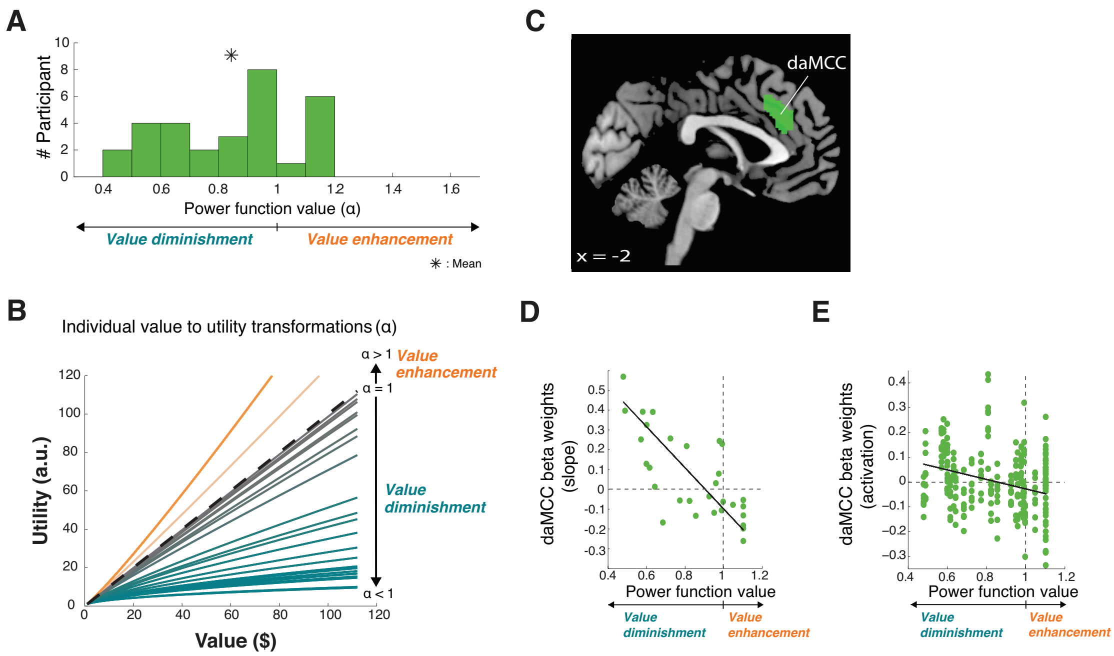

Figure 6.3. Value-to-utility transformation for gains. (A) Distribution of risk preferences in the gains domain as measured by power function values (α). (B) Distribution of individual value-to-utility transformations revealed by individual preferences. (C) Neural regions encoding the value-to-utility transformation. (D) Relationship between individual preferences and extracted daMCC beta values (slopes) from the covariate analysis. (E) Relationship between individual preferences and extracted daMCC betas values (activation) from the categorical model.

We found clear evidence that the vmPFC encodes parametric value signals for both the rEV and CV value formulations, with large overlap in the voxels identified for each of the two models (Figure 6.2A). We compared the quality of the fits for these formulations by extracting the beta values for each parametric value regressor from an unbiased 10mm spherical vmPFC region-of-interest (ROI) (x = -2, y = 40, z = -8), centered on the peak coordinate of parametric value signals reported in a meta-analysis study by Bartra and colleagues (1) (Figure 6.2B). The strengths of the representations of the rEV and CV value formulations were not significantly different from one another (t_{29} = .15, p = .88). The rCV formulation resulted in no significant voxels at the whole-brain level, and the ROI analyses confirmed that the strength of the encoding was not significantly greater than zero (t_{29} = 1.46, p = .15) and was significantly less than the rEV and CV formulations (rEV t_{29} = 2.03, p = .051; CV t_{29} = 2.90, p = .007).

Given the design of our task, with 15 trials for each of the 9 levels of the rEV formulation, we were able to visualize the actual neural encoding of the rEV formulation within the vmPFC ROI by extracting the beta values for each level of the rEV formulation (utilizing *GLM3*). The encoding of gains value signals in the vmPFC demonstrated a clear positive relationship between value and brain activation (Figure 6.2C). As the rEV and CV formulations equally well captured the value signals within the vmPFC, we chose to first focus analyses on the rEV factor. Post-hoc analyses demonstrate the congruence of results across both the rEV and CV formulations (below).

Identifying the neural encoding of the value-to-utility transformation, in gains.

The purpose of this project was to examine the neural mechanisms of the value-to-utility transformation. To do so required precisely quantifying the value-to-utility transformation that each participant was performing, captured based on their risk preference as expressed by their choices (modeled as the degree of curvature (α) of their individual utility function, a power function (Tymula et al., 2013)). In the gains domain, participants were on average risk averse (utility less than value, $mean \pm SD\ \ \alpha = .84 \pm .21$), with a wide range of preference values (Figure 6.3A).

Armed with the behaviorally derived quanitification of each individual's value-to-utility transformation, we sought the neural instantiation by covarying the value on each trial (rEV regressor here, and CV post-hoc below) against each individual's risk preference. This between-subject covariate analysis identifies neural regions that encode a linear value signal across trials, whose slope varies (positive to negative) based on the degree and direction of the value-to-utility transformation each individual is using to make their choices (Figure 6.3B). Whole-brain analyses revealed a significant fit to this function in voxels within the dorsal anterior midcingulate cortex (daMCC) (Bush, 2009) (Figure 6.3C; Table 6.5), in a region also referred to as the anterior midcingulate cortex (aMCC) (Vogt, 2005) or more generally as part of the dorsal medial prefrontal cortex (dmPFC).

Table 6.5. Neural encoding of the value-to-utility transformation across gains and losses

	# voxels	Regions	Hemisphere	Peak Coordinates *x*	*y*	*z*	*z-stat*
Gains rEV × α	794	Paracingulate Gyrus (referred to as daMCC, aMCC, or dmPFC)	L	-2	32	26	3.91
			R	2	26	36	3.87
			mid	0	32	30	3.83
	301	Supramarginal Gyrus	R	46	-44	56	3.21
			R	44	-42	46	3.1
			R	52	-46	54	2.99
Losses rEV × α	1055	Frontal Orbital Cortex	L	-44	30	12	3.32
		Frontal Pole	L	-28	54	0	3.83
		Inferior Frontal Gyrus	L	-42	14	24	3.29
	683	Paracingulate Gyrus (referred to as daMCC, aMCC, or dmPFC)	L	-6	28	26	3.73
			L	-2	22	38	3.57
		Superior Frontal Gyrus	L	-14	16	48	3.64
	482	Insular Cortex	L	-34	18	-6	3.79
		Frontal Orbital Cortex	L	-30	30	-10	3.56
			L	-44	28	-20	3.15
	362	Postcentral Gyrus	L	-42	-22	30	3.23
			L	-50	-14	38	3.2
		Precentral Gryus	L	-48	-14	46	3.08
	1645	Lingual Gyrus	R	20	-56	2	4.06
		Occipital Fusiform Gyrus	R	34	-66	-22	3.85
		Hippocampus	R	22	-26	-10	3.78
	1545	Supramarginal Gyrus	L	-28	-64	4	3.94
			L	-4	-62	-8	3.68
			L	-24	-56	-24	3.6
	675	Lateral Occipital Cortex	R	18	-68	58	3.77
			R	8	-72	60	3.18
		Procuneous Cortex	R	14	-64	33	3.19
	763	Lateral Occipital Cortex	L	-28	-80	42	3.33
			L	-14	-74	58	3.19
			L	-10	-70	60	3.12

Abbreviations: rEV, relative expected value; α , alpha; daMCC, dorsal anterior midcingulate cortex; aMCC, anterior midcingulate cortex; dmPFC, dorsomedial prefrontal cortex.
Regions are labeled based upon their Harvard-Oxford Atlas designations, with parenthetical inclusion of labels from text.
The coordinates for the three peak activations are provided for each cluster, in MNI space (in mm).

To examine the nature of the relationship between these indicated voxels and the value-to-utility transformation, we performed ROI analyses on the daMCC cluster, confirming a linear relationship between individual subjective value modulation and the extracted beta values from the covariate analysis ($r_{28} = -.73$, $p < .0001$) (Figure 6.3D). As the extracted beta values are derived from a parametric regressor (9 levels of rEV) they indicate the slope of the relationship between that regressor and daMCC activation. Interestingly, the resulting distribution of beta values is zero-centered with positive betas (slopes) for value diminishment and negative betas (slopes) for value enhancement.

Given the complexity of the covariate analyses, we sought to clearly describe the relationship between daMCC activation and the value-to-utility transformation – how modulated daMCC activation/deactivation corresponds to reduced/enhanced subjective valuation. We anticipated finding the same zero-centered negative relationship as apparent in the covariate ROI analysis. To confirm this relationship, for each participant we extracted their daMCC activation level for each of the 9 levels of the categorical rEV regressors (from *GLM3*), and across participants, regressed these values against each individual's risk preference (a 270 point fit). The solution was significant ($F_{1,268} = 13.02$, $p < .001$) with a slope of -.13 ($SEM = .036$) and an intercept of .11 ($SEM = .031$). The negative slope confirms the overall relationship between daMCC activation and the value-to-utility transformation – the more activated the daMCC is the more diminished the subjective value will be (and the reverse). Further, based on the intercept we can calculate the daMCC activation at risk neutrality (α = 1) to be -.02, which is within 1 *SEM* from zero, confirming the zero-centeredness of this function (Figure 6.3E).

Enhanced activation in the daMCC corresponds to diminished subjective valuation, deactivation of the daMCC corresponds to enhanced subjective valuation, and baseline daMCC corresponds to non-modulation of subjective valuation (utility = value). This near-zero-centered bi-directional function provides a perfect substrate for the value-to-utility transformation.

Replicating the neural encoding of the value-to-utility transformation, in losses.

For the within-study replication, we repeated our analyses in the intermixed losses trials. On average, participants were risk neutral (*mean* ± *SD* α = 1.04 ± .26) (Figure 6.4A), with a range of preferences. There was no significant correlation between individual risk preferences across the gains and losses domains (r_{28} = .26, p = .16), concurring with recent studies (Kurnianingsih & Mullette-Gillman, 2015; Kurnianingsih et al., 2015; Mullette-Gillman, Kurnianingsih, & Liu, 2015; Mullette-Gillman, Leong, & Kurnianingsih, 2015). We then replicated our analyses to identify the regions encoding the value-to-utility transformation, covarying the rEV value regressor by individual preferences (Figure 6.4B). These whole brain analyses identified a significant cluster within the daMCC encoding the value-to-utility transformation each individual was performing, replicating the results in the gains domain (Figure 6.4C and Table 6.5). ROI analysis within the daMCC revealed a clear linear relationship between value modulation (risk preference) and daMCC betas (losses: $r_{28} = .64$, $p < .001$) (Figure 6.4D). In near-perfect agreement with the function found for gains, positive daMCC betas correspond to value diminishment, negative betas correspond to value enhancement, and daMCC betas of zero correspond to no value modulation (α = 1).

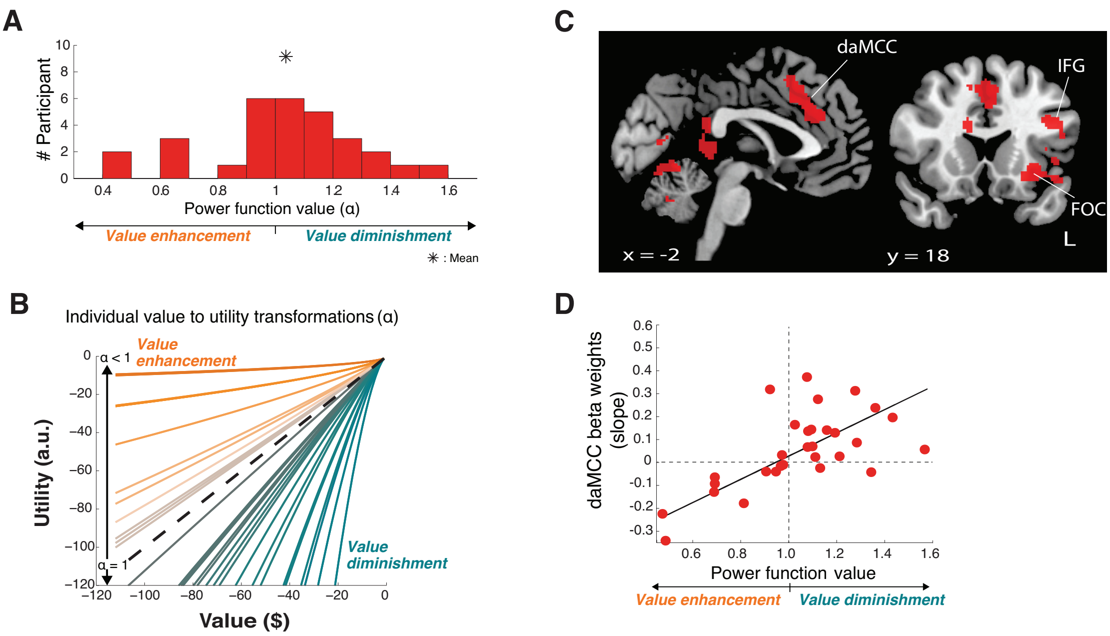

Figure 6.4. Value-to-utility transformation for losses. (A) Distribution of risk preferences in the losses domain as measured by power function values (α). (B) Distribution of individual value-to-utility transformations revealed by individual preferences. (C) Neural regions encoding the value-to-utility transformation. (D) Relationship between individual preferences and extracted daMCC beta values (slopes) from the covariate analysis. Note the inverted relationship between risk preference and value modulation across gains and losses (compare x-axes of Figure 6.3D and 6.4D) resulting in matched relations between daMCC beta values and the sign and degree of the value-to-utility transformation.

Critically, these results confirm that the information for the value-to-utility transformation localizes to the daMCC (Figure 6.5). Across both our initial investigation within the gains domain and the replication in the losses domain, we not only identified the same brain region across whole-brain analyses but also independently identified the same zero-centered functional relationship between the daMCC (slopes and activation) and the degree/direction of the value-to-utility transformation.

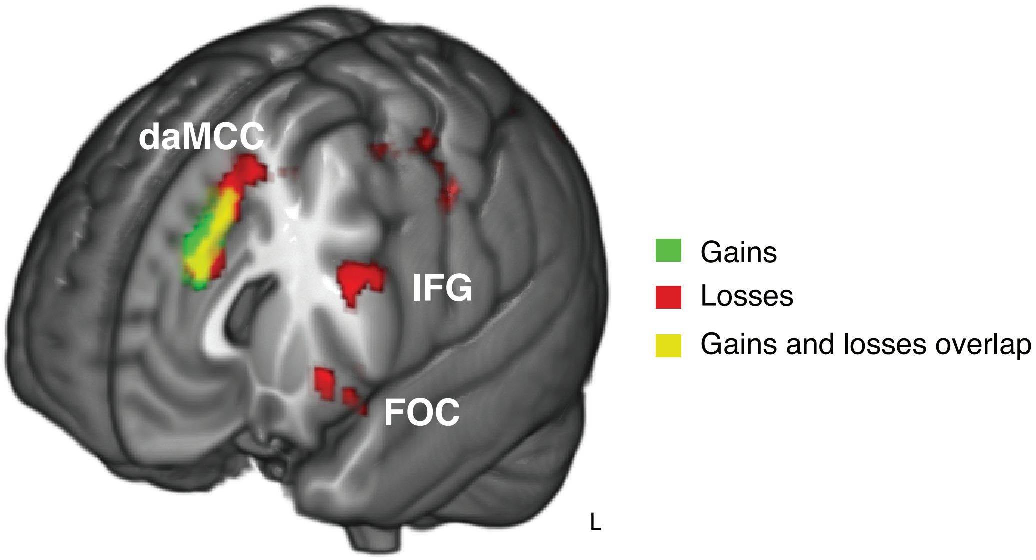

Figure 6.5. Overlap of regions encoding the value-to-utility transformation information across gains (Figure 6.3C) and losses (Figure 6.4C).

Identifying brain regions involved in the value-to-utility transformation through functional connectivity analyses.

We examined the network of brain regions that communicate during the value-to-utility transformation, through functional connectivity analyses. To identify brain regions that have task-related functional connectivity with the daMCC during risky choices, psychophysiological interaction (PPI) analyses were performed separately for the decision periods of risky gains and losses trials, with a seed ROI from the daMCC (produced through a conjunction analysis across gains and losses, between Figure 6.3C and 6.4C). This analysis identified only two brain regions with significant functional connectivity with these daMCC voxels. The daMCC is positively connected to the left inferior frontal gyrus (IFG) and negatively connected to the nucleus accumbens (NAcc) (Figure 6.6A–C and Table 6.6).

Table 6.6. Brain areas exhibiting significant functional connectivity with the dmPFC seed region during the decision period of risky vs. certain trials within each domain.

		# voxels	Region	Hemisphere	Peak Coordinates			*z-stat*
					x	*y*	*z*	
Gains	Positive	286	Inferior Frontal Gyrus	L	-44	28	18	3.56
				L	-40	30	10	3.45
				L	-38	20	16	3.23
	Negative	390	Angular Gyrus	R	38	-56	44	4.03
			Lateral Occipital Cortex	R	40	-62	52	3.79
				R	36	-60	56	3.2
		2568	Occipital Pole	R	6	-92	6	4.43
				L	-6	-100	0	4.29
				L	-8	-98	6	4.2
Losses	Positive	359	Inferior Frontal Gyrus	L	-38	24	20	3.54
				L	-52	18	30	3.52
				L	-46	28	18	3.1
	Negative	347	Frontal Orbital Cortex	L	-20	16	-14	3.36
				L	-14	16	-12	3.22
			Putamen	L	-26	-2	2	3.34
		513	Lateral Occipital Cortex	R	34	-62	48	3.62
				R	42	-60	46	3.45
				R	38	-62	50	3.39
		1847	Occipital Pole	L	8	-100	0	4.09
				L	-6	-94	14	3.98
			Lingual Gyrus	L	-2	-74	2	4.07

Regions are labeled based upon their Harvard-Oxford Atlas designations. The coordinates for the three peak activations are provided for each cluster, in MNI space (in mm).

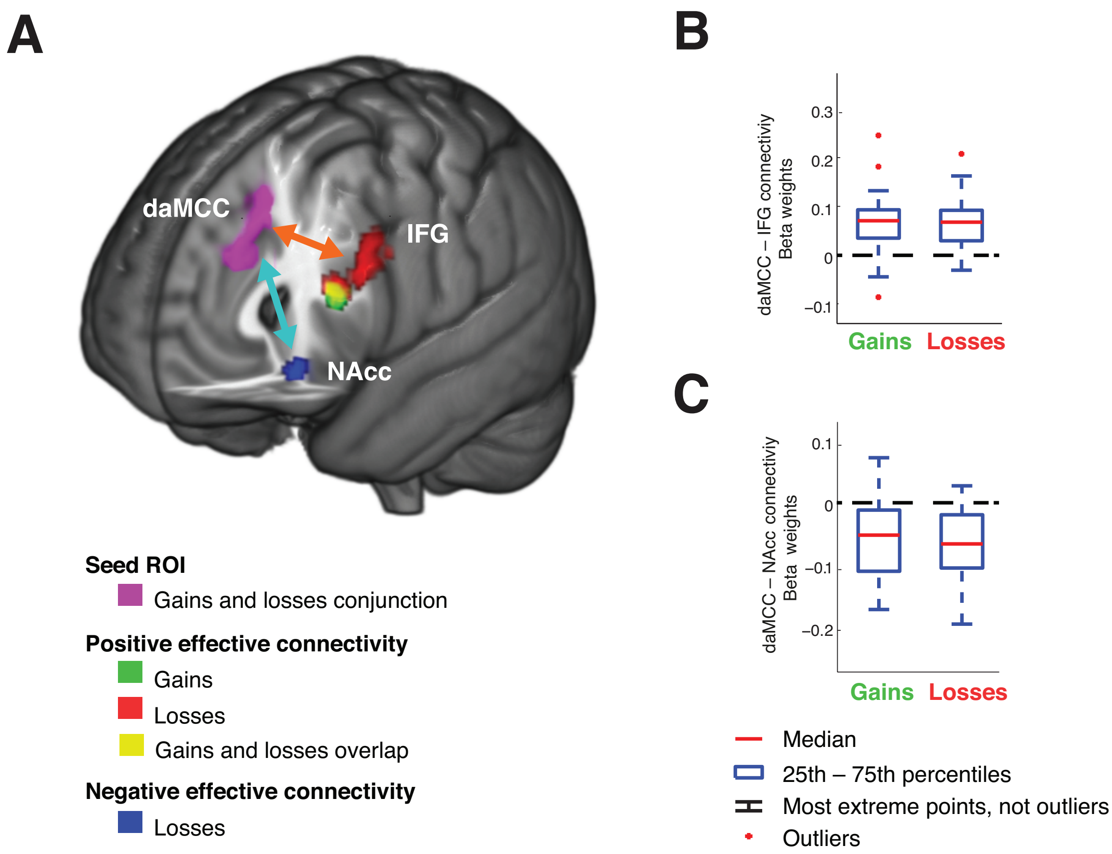

Figure 6.6. Functional connectivity of the daMCC during decision making. (A) Brain areas with decision-related functional connectivity to the daMCC. The daMCC has whole-brain significant positive connectivity to the left IFG for both gains and losses and negative connectivity to the NAcc for losses. (B) Connectivity between daMCC and IFG, extracted from the conjunction of the significant voxels in the IFG for both gains and losses. (C) Connectivity between daMCC and NAcc, extracted from the losses NAcc region. ROI analyses revealed significant functional connectivity in the NAcc for gains ($t_{29} = 5.01$, $p < .0001$) (for boxplot: red line is median, blue solid box indicates the 25 to 75 percentile, error bar indicates the range of non-outlier extreme values, '+' indicates outliers).

Post hoc replication of the value-to-utility covariate analyses with alternative value and preference metrics.

Our analyses demonstrate that the daMCC encodes the information necessary for the value-to-utility transformation. These results were obtained using a specific formulation for the value on each trial (rEV) and a common measure of individual risk preferences (α). To test the robustness and generalizability of the encoding of value subjectifcation in the daMCC, we repeated our analyses using an alternative formulation of value (chosen value, CV) and an alternative metric for quantifying individual risk preferences (risk premium, a linear formulation) (Stanton et al., 2011; Mullette-Gillman, Leong, & Kurnianingsih, 2015; Mullette-Gillman, Kurnianingsih, & Liu, 2015; Kurnianingsih & Mullette-Gillman, 2015; Kurnianingsih et al., 2015). These alternatives extend our analyses from simply across gains and losses to an additional 2×2 space across risk preferences (α and premium) and value formulations (rEV and CV). The goal is to examine whether the relationship between daMCC activation and value subjectification is robust across these alternative ways of quantifying components of value subjectification.

Alternative risk preference measure: Risk premium. We additionally quantified each individual's risk premium using psychophysical indifference point analyses (for details see Mullette-Gillman, Leong, & Kurnianingsih, 2015; Mullette-Gillman, Kurnianingsih, & Liu, 2015; Kurnianingsih & Mullette-Gillman, 2015; Kurnianingsih et al., 2015), which measures the degree and direction of value subjectification in a zero-centered multiplicative/linear form (as compared to the one-centered power function form of the α risk preference metric). Although these metrics have different theoretical assumptions, we find strong correlations between them in this study (gains: $r_{26} = -.74$, $p < .0001$; losses: $r_{27} = -.45$, $p < .0001$) and previous studies (Mullette-Gillman, Leong, and Kurnianingsih, 2015; Mullette-Gillman, Kurnianingsih, and Liu, 2015; Kurnianingsih and Mullette-Gillman, 2015; Kurnianingsih et al., 2015; Stanton et al., 2011).

Alternative value regressor: Chosen value. The CV regressor was constructed as the value of the chosen option on each trial, and was previously included in *GLM2b* and ROI analyses comparing the degree to which the vmPFC encodes different formulations of value regressors. Of note, these analyses indicated that the vmPFC equally encodes both the rEV and CV formulations of valuation.

ROI analyses. In our main analyses, we identified a daMCC region as the conjunction of value subjectification across both the gains and losses domains. We performed ROI analyses on this region to visualize the relationship between daMCC beta values and value subjectification. We then repeated this analysis three more times, to produce a 2×2 set of analyses, defined by the selected formulation of value on one side and the selected risk preference metric on the other. Within each of these four cells, we examined the relationship independently for the gains and losses domains – resulting in a total of eight scatterplots and correlations (Figure 6.7).

Robustness of value subjectification in the daMCC. In the gains domain, we find significant correlations between daMCC beta values and individual risk preferences for all four pairings of value metrics and risk preference metrics (Figure 6.7; Table 6.7). In the losses domain, statistical significance is only present for the initially performed rEV and power function pairing, however, all four of the losses pairings show the same relationship between value subjectification (enhancement or diminishment) and daMCC beta values, with correlation coefficients greater than |.2|. This clear consistency across metrics demonstrates the robustness of the encoding of value subjectification in the daMCC.

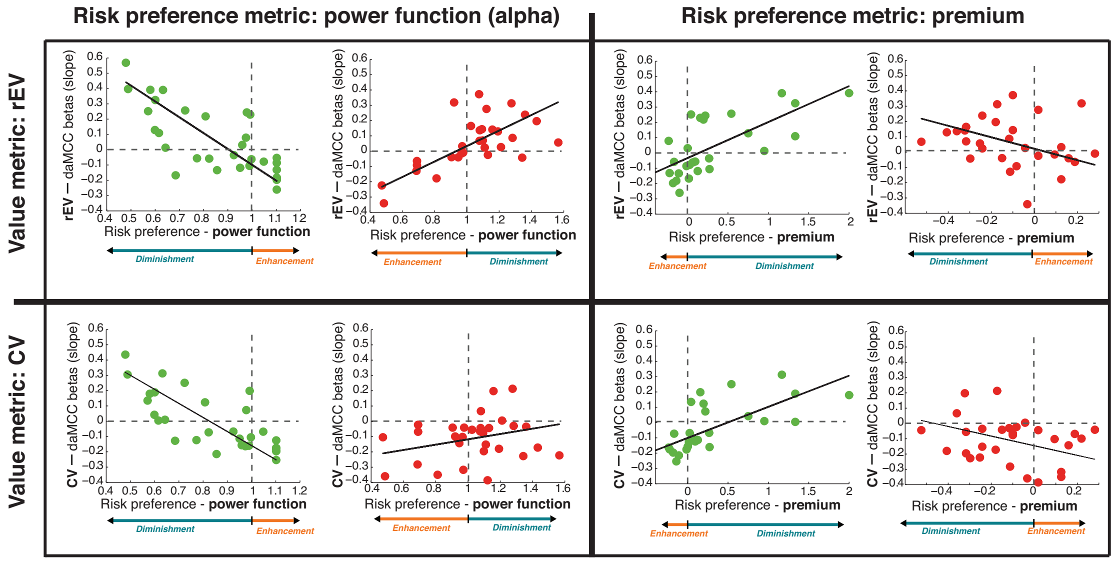

Figure 6.7. Relationship between individual preferences and daMCC betas (slopes) across alternative formulations of value and risk preference. Results from Figure 6.3C and 6.4C (in top left cell; gains in green and losses in red) were tested for robustness across a 2×2 space. Note that the relationship between risk preference and value subjectification is inverted across gains and losses, and also across the two risk preference measures. For each graph, the relation of the preference metric and value subjectification is shown in color at the bottom. Of note, all eight subplots show the same relationship between daMCC betas and value subjectification – increasing for value diminishment and decreasing for value enhancement.

Table 6.7. Testing the robustness of value-to-utility transformation encoding in the dmPFC – correlations between dmPFC ROI beta values and individual preferences, across two formulations of value (rEV and CV) and two measures of risk preference (power function and premium).

		Risk Preference Metric	
		Power Function	Premium
[Value] regressor formulation	rEV	Gains: $r = -.73$, $p < .0001$ Losses: $r = .64$, $p < .0001$	Gains: $r = .68$, $p < .0001$ Losses: $r = -.22$, $p = .24$
	CV	Gains: $r = -.75$, $p < .0001$ Losses: $r = .22$, $p = .24$	Gains: $r = .65$, $p < .0001$ Losses: $r = -.23$, $p = .21$

Abbreviations: rEV, relative expected value; CV, chosen value.
Expanding from rEV [Value] regressor covaried by power function risk preference metric (top left cell of correlations) to 2×2 of [Value] by [Risk Preference]

Post hoc replication of the value-to-utility covariate analyses within trials with two certain options.

Our initial and replication analyses indicate that the daMCC encodes the degree and direction of value subjectification on a trial-by-trial basis, that it represents the currently engaged value-to-utility transformation across intermixed gains and losses trials. To strengthen this relationship, we tested the context-specificity of this encoding – hypothesizing that the daMCC would not encode the risk-based value-to-utility transformations on the trials in which participants are comparing the value of two certain options. As this analysis covaries individual risk preferences against the trial value regressor on trials in which risk is absent, there is an expectation that risk preferences will not be significantly encoded within the daMCC on these trials, even though we have demonstrated that it is present during the intermixed gains and losses trials with risk. These analyses were performed replicating the rEV regressor for gains and losses within trials with two certain options, for each domain, and covarying the rEV regressor of each domain by the corresponding risk preference of each participant. Whole-brain analyses identified no voxels with significant relations. In addition, ROI analyses were performed on the daMCC ROI, revealing no significant relationship between daMCC beta values and individual risk preference values (gains: r_{28} = -.15, p = .42; losses: r_{28} = .16, p = .41). This analysis indicates that the value-to-utility transformation encoded by the daMCC is context specific, and that this information is not significantly represented outside of the appropriate context. In short, the daMCC encodes the information necessary to compute the value-to-utility transformation that is currently being performed.

Identifying the neural encoding of parametric *losses: No whole-brain significant voxels and no significant encoding in the vmPFC ROI*. We investigated the neural encoding of linear value signals for losses. For all of three parametric formulations of the value on each trial (rEV, CV, rCV), whole-brain analyses (utilitizing *GLM2a, b, c*) identified no voxels with a significant relationship between reduced activation and reduced value. We tested the encoding of linear loss value signals within the vmPFC through ROI analyses using the same unbiased 10mm spherical vmPFC ROI (x = -2, y = 40, z = -8) used in gains, extracting the beta values for each value formulation. None of these formulations of loss value were significantly encoded within the vmPFC (t_{29} < .75, p > .46) (Figure 6.8A).

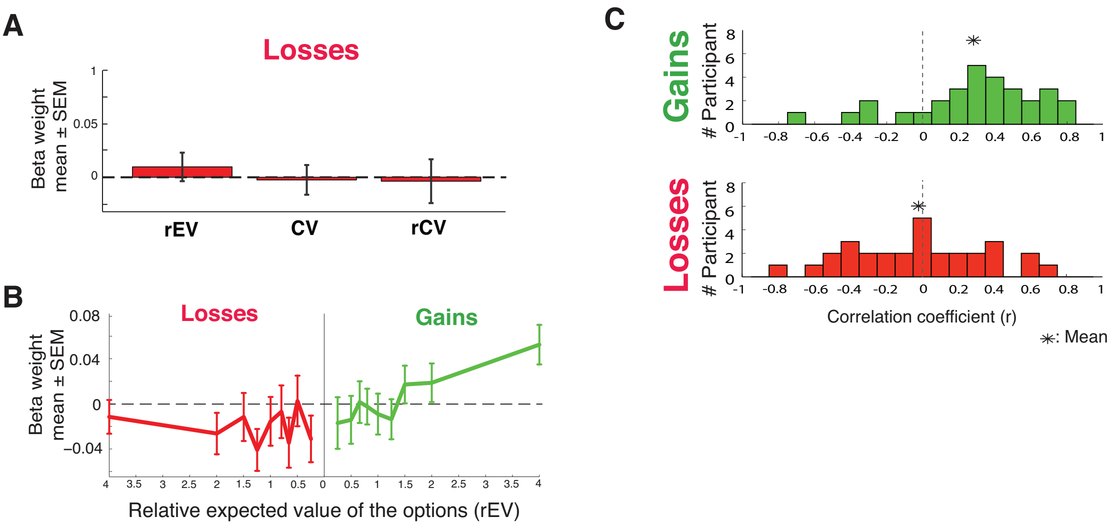

Figure 6.8. Neural encoding of value in losses. (A) ROI analyses measuring the encoding of three different value formulations (relative expected value, rEV; chosen value, CV; relative chosen value, rCV). (B) Functional encoding of value in the ventromedial prefrontal cortex (vmPFC), across gains and losses. Beta weights indicate vmPFC activation for each rEV value. (C) Distributions of the correlation between each individual's beta weights against the rEV values.

To confirm the absence of a loss value signal in the vmPFC, we extracted and plotted the actual value function encoded within the vmPFC ROI, replicating our previous method in the gains domain. In brief, we extracted the activation for each of the nine rEV levels across losses (utilizing *GLM3*) from the same vmPFC ROI used previously. While gains presented a clear positive monotonic function relating the rEV to brain activation levels within the losses domain the function is flat, showing no relationship between brain activation and value across the rEV levels (Figure 6.2C and Figure 6.8B).

As a final step, we investigated the encoding of value signals within each individual, correlating their individual activation for each rEV against the rEV values (separately for gains and losses) (Figure 6.8C). In gains, this correlation analysis revealed a clear positive average correlation in the gains domain (*mean* ± *SD* $r = .28 \pm .36$, difference from $r = 0$: $t_{29} = 4.27$, $p < .0001$). In losses, this correlation analysis revealed a mean-zero distribution with a near uniform distribution, save a large peak at zero (*mean* ± *SD* $r = .02 \pm .39$, difference from $r = 0$: $t_{29} = 1.22$, $p = .23$).

Discussion

The daMCC encodes the context-specific information necessary to perform the value-to-utility transformation, as demonstrated through highly specific modeling and confirmed with in-task replication. Further, we specify that, for a given value, enhanced activation of the daMCC corresponds to value diminishment and deactivation of the daMCC corresponds to value enhancement. These results provide a specific and novel functional role in decision making for the daMCC (also referred to as the aMCC or dmPFC) (Bush, 2009; Vogt, 2005).

Previous studies have implicated the daMCC/dmPFC in decision making, with a range of potential roles from outcome evaluation (Botvinick, 2007), decision conflict (Botvinick, Cohen & Carter, 2004; Pochon et al., 2008), reward prediction error (Rushworth & Behrens, 2008), strategic preference (Venkatraman et al., 2009), or degree of uncertainty (Christopoulos et al., 2009). Notably, although Pochon and colleagues beautifully demonstrated that this same region (which they referred to generically as anterior cingulate cortex) is involved in decision making rather than motor planning (Pochon et al., 2008), their task and analyses could not differentiate between a number of co-occurring cognitive processes, ranging from attention, memory, theory of mind, and even face processing. In fact, their full results suggest that their decision conflict analysis may have reflected all of these cognitive processes, as they identified parametric encoding of decision conflict in numerous brain regions (including the dorsolateral prefrontal cortex, parahippocampal gyrus, fusiform gyrus, and even striate visual area) (Pochon et al., 2008). In contrast, the high precision of our between-subject covariate analyses (a 270-point fit [9 levels of rEV covaried by the preference values of 30 participants], with 15 trials per point) safeguards our results from being the result of co-occurring cognitive processes – the specificity of the computational model allows specificity of the identified cognitive processes. We note explicitly that our results cannot be due to choice difficulty, as the value-to-utility functions fit are orthogonal to choice difficulty (as both a within- and between-subject fit). Further, choice difficulty is not a cognitive process or computation, but rather is a comparison of task states that reflects the need for greater computations to compare across options to reach a decision (i.e., a comparative need for greater processing, but not what those processes are). Our precise analyses suggest a specific computation that is occurring within the daMCC - that the daMCC encodes the information necessary to perform the value-to-utility transformation. We note that a potential reconciliation of these results is that choice difficulty reflects greater required precision of the value-to-utility transformation.

Even with the high specificity of our analyses, they cannot provide causal evidence of the role of the daMCC in the value-to-utility transformation. However, a recent study has indicated that activation patterns within a proximal dmPFC region can predict risky decision making prior to the presentation of the available options (Huang et al., 2014). The predictive power of this information suggests causal evidence – that is, varied activation patterns within the daMCC can modulate how not-yet-presented stimuli will be judged. Our study suggests an intriguing mechanism for this predicted choice behavior: that fluctuation in the daMCC prior to option presentation may modulate the value-to-utility transformation of the incoming options, altering their computed utilities and therefore biasing choice behavior.

Our functional connectivity analyses indicate the functional network of regions with which the daMCC communicates during risky decision making – the IFG and NAcc. Although these analyses cannot inform on the directionality of signals, given the known role of the NAcc in valuation (Abler et al., 2006; Knutson et al., 2011; Knutson et al., 2005; Peters & Büchel, 2010), and IFG's role in executive processing and working memory (Duncan & Owen, 2000; Mullette-Gillman & Huettel, 2009), we hypothesize that the value-to-utility transformation within the daMCC is 'set' contextually by inputs from the IFG, and outputs to modulate value signals within the NAcc.

We see an excellent substrate for the value-to-utility transformation in the interactions of the daMCC and NAcc, combining across the value-to-utility transformation covariate analyses and the functional connectivity analyses. Our covariate analyses demonstrate that the daMCC activation has a zero-centered negative relationship with the degree of the value-to-utility transformation – daMCC activation results in reduced subjective valuation, daMCC deactivation results in enhanced subjective valuation, and baseline daMCC activation (non-modulated) results in non-modulated subjective valuation (i.e., subjective value = objective value). Numerous studies have shown that the activity of the NAcc is positively correlated with reward value (Knutson et al., 2011; Knutson et al., 2005; Peters & Büchel, 2010). The negative functional connectivity identified between the daMCC and NAcc, and the presence of value signals within the NAcc, combine to suggest that inhibitory or excitatory signals from the daMCC to NAcc could drive altered subjective valuation. Simply, our results suggest that subjective valuation could be the result of daMCC activation inversely modulating valuative processes in the NAcc.

Conclusions

In conclusion, we identify the neural instantiation of the value-to-utility transformation within the daMCC. Further, we describe a simple network of regions through which contextual information (contingency and long-term history) could be integrated to determine the gain of the value-to-utility transformation and modulatory signals could be output to alter valuation signal.

Chapter 7: General Discussion

Summary

In this dissertation risky monetary decision making was investigated to understand the neural mechanisms underlying choice behavior by looking at how individuals modulate subjective value across monetary gains and losses in response to outcome uncertainty. The studies in this dissertation looked at behavioral measures of risk preferences and choice strategy, how different state modulations alter these behavioral measures, the relationships and differences between these behavioral measures in the gains and losses domains, and the neural mechanism of the value-to-utility transformation of decision making.

The effects of aging, sleep deprivation, and cognitive fatigue on uncertainty preferences and choice strategies under both the gains and losses domains were investigated. Across the three different states, we found that: 1) aging alters uncertainty preferences and choice strategy for losses; 2) sleep deprivation alters choice strategy for gains; 3) cognitive fatigue reduces stability in uncertainty preferences and choice strategy in both domains. Aging, sleep deprivation and cognitive fatigue have all been found to produce deleterious effect on executive function and vigilance (Berardi, Parasuraman, & Haxby, 2001; Pang et al., 2006; Persson et al., 2007; Lim & Dinges, 2008). Although no study has directly compared the neural mechanism across these states, our studies suggest clear dissociation between the effects of aging, sleep deprivation and cognitive fatigue on economic decision making and that they do not affect the neural mechanisms of decision making in the same manner (see summary in Table 7.1). Furthermore, our findings suggest that aging and sleep deprivation are more likely to affect neural mechanisms that do not overlap between gains and losses decision making, as both produced different effects in the gains and losses domains, while cognitive fatigue affects neural mechanisms that overlap between gains and losses decision making, as cognitive fatigue had similar effects in both domains. Unfortunately, due to the complexity of decision making, it remains difficult to identify or infer what specific neural mechanisms or brain regions are altered by these different states just by looking at behavioral alterations in risk preference and choice strategy without any direct neuronal investigation.

Table 7.1. Dissociable effect of aging, sleep deprivation, and cognitive fatigue on economic decision making

	Aging	Sleep Deprivation	Cognitive Fatigue
Gains			
Risk preference	-	-	Less stable
Ambiguity preference	-	-	-
Strategy	-	Less maximizing	Less stable
Use of rEV information	-	Decreased	-
Use of pWIN information	-	Increased	-
Losses			
Risk preference	More risk averse	-	Less stable
Ambiguity preference	More risk averse	-	-
Strategy	Less maximizing	-	Less stable
Use of rEV information	Decreased	-	-
Use of pWIN information	-	-	Less stable

Abbreviations: pWIN, probability of winning; rEV, relative expected value.

Across the three state modulation studies, there was no correlation between gains and losses found, suggesting that they are independent from each other. This motivated further investigation about the differences and similarities between gains and losses decision making. Several behavioral and neural differences and similarities between gains and losses decision making were found, suggesting that they are the result of both dissociable and overlapping cognitive/neural mechanisms (see summary in Table 7.2.). Behaviorally, the classical pattern of risk preferences was replicated – across all studies participants were risk averse in the gains domain and risk seeking/neutral in the losses domain demonstrating the existence of the reflection effect within the aggregate level on average across participants (Prospect Theory; Kahneman & Tversky, 1979). On the contrary, within the individual level, we repeatedly found no correlation between individual gains and losses risk preferences across studies when gains and losses trials were given separately. We further tested the correlation between gains and losses risk preferences using a larger sample with an intermixed-trial task design, where subjects were asked to repeatedly call up their gains and losses risk preferences. The absence of correlation still remained suggesting independence. Interestingly, although there were no significant correlations between gains and losses risk preferences, we found that cross-domain risk preferences had predictive power over choice behavior that were significantly better than chance and that in both domains, the more participants relied on the maximizing choice strategy, the more risk neutral they were (equating value and utility maximization).

Table 7.2. Summary of main results across all studies showing the differences and similarities between gains and losses decision making

	Differences	Similarities
Behavioral Risk preference	1) On average, people are risk averse in the gains domain and risk	1) Cross-domain risk preferences have predictive power over

	seeking/neutral in the losses domain 2) Only losses domain risk preference is altered by aging, with older adults being more risk averse	choice behavior 2) Cognitive fatigue reduces stability in risk preferences in both domains
Choice Strategy	1) People rely more on the use of the more maximizing strategy in the losses domain 2) Only gains domain choice strategy is altered by sleep deprivation with lesser use of the maximizing strategy and more use of the satisficing strategy	1) Cognitive fatigue reduces stability in choice strategy in both domains
Neural Value signal encoding	1) The vmPFC encodes value signal for gains, but not for losses	
Value-to-utility transformation		1) The same neural instantiation of the value-to-utility transformation is in overlapping areas in the daMCC for both domains 2) The daMCC has positive functional connectivity with the IFG and negative functional connectivity with the nucleus accumbens during decision making in both domains.

Abbreviations: daMCC, dorsal anterior midcingulate cortex; IFG, inferior frontal gyrus; rEV, relative expected value.

Using fMRI, we were able to localize the neural instantiation of the value-to-utility transformation to the daMCC and found large overlapping regions encoding the value-to-utility transformation across gains and losses. Furthermore, similar patterns of functional connectivity were identified across the gains and losses domains. In both domains, the daMCC has positive functional connectivity with the IFG and negative functional connectivity with the nucleus accumbens. Besides these neural similarities, we found differences in the neural encoding of value signals for gains and losses. While we found linear value signal for gains encoded in the vmPFC, we found no significant evidence for linear value signal for losses encoded in the brain.

In the following sections risk preference, the encoding of value signal, the value-to-utility transformation and the possibility of exploring other domains are further discussed.

The consistency of risk preference across contexts

There are several evidence in our findings showing that risk preferences are not the result of a single neural mechanism. First, if risk preferences were indeed the result of the same neural mechanism, we would have found high correlations between gains and losses risk preferences (especially in the intermixed-trial design). On the contrary, we did not find any significant correlations between gains and losses risk preferences across all our behavioral studies ($r(200) = .12$, $p = .094$). The low correlation coefficients between gains and losses risk preferences show that most of the variances in gains and losses risk preferences do not come from the same source – in opposition to the reflection effect which suggests strong underlying connection between gains and losses risk preferences. Second, we found that aging alters risk preferences in the losses domain but not in the gains domain and that aging and cognitive fatigue do not alter risk preference in the same manner. These differential alterations of risk preferences show that there are multiple neural mechanisms that can influence our risk assessment and preference, and that different factors can influence different neural mechanisms that shape our preferences.

Although our results show that gains and losses risk preferences are not the results of the same underlying neural mechanisms, the results also show that they are not completely independent from each other. As supporting evidence, cognitive fatigue does not differentially alter risk preference, choice strategy or test re-test risk preference stability. Moreover, cross-domain risk preference still had predictive power over choice behavior that was significantly better than chance or than scrambling the relationship between within-domain risk preference and choices across participants. The proposed similarities and differences in the underlying cognitive and neural mechanisms seem to be able to explain the inconsistencies in many studies that have suggested that risk preferences are independent across domains/contexts (e.g. Weber et al., 2002; Soane & Chimel, 2005), while several other studies have suggested that individual's overall attitude toward risk should be stable across domains/contexts (e.g. Weber & Milliman, 1997; Lusk & Coble, 2005; Soane & Chimel, 2005; Weber & Johnson, 2008; Einev et al., 2010). The closeness of the interrelationships across domain risk preferences may be influenced by the relatedness of the components and decision making factors contributing to the formation of risk preference.

The generalizability of the linear value signal in the vmPFC – absence of linear value signal for losses

The value scale ranges from positive to negative values. As positive neural correlates of value signal can also be interpreted as increase in attention/arousal, the finding for a positive value signal cannot immediately be generalized to the losses domain without being empirically tested. In our fMRI study, we were able to find the neural encoding of value signal for gains in the vmPFC, but found no evidence of the neural encoding of value signal for losses in the brain (Chapter 6). While over 200 neuroimaging studies clearly and robustly show that activation within the vmPFC encodes value signal for gains (Bartra et al., 2013; Clithero & Rangel, 2014), there are only three studies that suggest that the vmPFC also encodes value signal for losses. In all three, there are reasons to doubt the generalizability of their results, ranging from the unjustified re-coding of low gains as losses (Plassmann et al., 2010; Litt et al., 2011) to a potential interaction from the use of mixed gambles (Tom et al., 2007). Another difference is that, unlike our decision task, the tasks in these three studies (Tom et al., 2007; Plassman et al., 2010; Litt et al., 2011) did not involve comparison or calculation between options as each trial only required evaluation of a single item.

It remains unclear whether losses values are encoded in the same way gains values are encoded in the brain. Behaviorally, in the losses domain, we have consistently shown increased reliance on the rEV information (the more maximizing and deliberative choice strategy). In more difficult decisions requiring more deliberative cognition, activation in the vmPFC (linked to the valuative/affective system) has been found to be weaker in easier decisions

(Rolls et al., 2010). Previous studies have also shown that simple numerical value comparisons (which only involve count but not worth) do not show increase or value-related activation in the vmPFC (Kadosh et al., 2005; Hunt 2012; in trials with certain vs. certain options in Chapter 6). Although it may seem possible that decisions in the losses domain are only treated as simple numerical value comparisons, this is less likely to be the case in our study, as the same neural instantiation of the value-to-utility transformation found in the gains domain was also found in the losses domain.

Another possible explanation for the asymmetry of value encoding in the vmPFC is that the vmPFC encodes an integrated value signal that incorporates both gains and losses, but is limited to positive final values or the final value comparison between losses value and gains value. If so, this signal would be present for trials with only gains and mixed trials, but would show no value signal in trials with only losses values. Such a result would suggest that the vmPFC signal is not a truly multipurpose value signal, but rather expresses the 'approach motivation' of the options (how much you like the option you are selecting). The possibility of such a result is suggested by behavioral differences between approach and avoidance behaviors, i.e. while gains (or rewards) lead to graded approach behaviors, losses (or punishment) often leads to all-or-nothing behaviors (such as choosing not to act/choose at all or even flight). In other words, while there is evolutionary value in encoding varying degrees of gain, it may be that negative values are simply motivationally categorized as 'avoid'. Of note, we can certainly use math to make decisions between any numbers of any sign, however the motivational system may not have been evolved to care about truly negative prospective options as in most cases, in our evolutionary past, we had the option of avoiding them. This result would suggest a deep insight into motivated behavior and decision making.

The generalizability of the value-to-utility transformation in the daMCC/dmPFC

We localized the neural instantiation of the value-to-utility transformation to the daMCC/dmPFC in our fMRI study using a within-study replication across the gains and losses domains (Chapter 5). An intriguing question is that if it is true that losses are simply avoidance or comparison between counts, why do we still perform the value-to-utility transformation for losses? Some possible explanations would be, first, our task does not allow participants to avoid choosing as they were all forced trials where participants had to consider and choose between the given options. It is therefore impossible to simply avoid both options in the task. Second, even though losses decision making might not involve so much of the valuative system as in the gains domain, especially when no evidence of losses value signal was found in the vmPFC, the choices could not have been based on just counts as participants still had to weight the riskiness of each gamble. If participants only calculated the expected value of the gambles to make their comparisons, they would all be risk neutral. Instead we see variability in losses risk preferences across participants. This shows that many of them were actually modulating their utility of the options due to the risk/uncertainty of the outcome. In contrast, in the certain vs. certain trials where no risk was involved and simple comparison between counts was sufficient for choosing the best option, we found no evidence of the value-to-utility transformation being performed in either the gains or losses domain.

Exploring other forms of monetary decision making

The studies in this dissertation focused on risky decision making, specifically looking at risk preference, choice strategy, and the neural mechanism of subjective value modulation across the gains and losses domains. Just as subjective value can be modulated by risk, subjective value can also be modulated by other factors, including time and effort, and the degree of value modulation can be different across the gains and losses domains. It would be interesting to investigate other forms of monetary decision making. Prior studies have found differences between gains and losses decision making in temporal discounting where people tend to discount the subjective value of delayed gains significantly more than delayed losses (Estle et al., 2006), and in effort discounting where people are more willing to expend more effort to avoid losses than to gain the same amount, showing that they value losses more than gains of the same amount (Hannan, Hoffman, & Moser, 2005). Although this dissertation provides evidence of independence between gains and losses risk preferences, it is unclear whether we would also see this independence between the gains and losses in temporal discounting or effort discounting. It would also be interesting to investigate the generalizability of the value-to-utility transformation in the daMCC/dmPFC – whether we can still find value signal whose slope is dependent on how much an individual is modulating value based on these other factors.

The value-to-utility modulation in other domains

As part of our executive function, the value-to-utility transformation is not only specific to monetary decision making. Value modulation is commonly seen in other domains as well. For example, aesthetic values of artworks are modulated by different context such as whether they are seen in daily life or in an art gallery (Kirk et al., 2009), attractiveness of faces are modulated by social context such as the beliefs and attitudes of others (Zaki, Schirmer & Mitchell, 2010), food reward processing is modulated by hunger and satiety (Siep et al., 2009), and moral judgment is modulated by disgust (Wheatley & Haidt, 2005; Ong, 2014). As such, it would be interesting to investigate whether activation in the daMCC/dmPFC associated to value modulation could be replicated in other domains beyond the monetary domain. As an initial step, in a recent study where we investigated the neural circuitry of moral judgment modulation by disgust priming, we found that individual change in moral acceptability between disgust and neutral priming conditions covaried with individual differences in activation in the dmPFC (which is in close proximity to the daMCC/dmPFC region found in Chapter 6) (Lim et al., in sub), suggesting that the value-to-utility mechanism is also involved in other domains.

Limitations

There were several limitations in the studies in this dissertation. First, there exists several potential confounds in the state modulation studies. For example, in the aging study, the demographics of younger and older adults population do not allow the match of factors that are mostly associated with age and cohort, such as educational level, marital status and economic status. In the sleep deprivation study design, there were time differences between the RW and SD sessions that might have affected the results. Second, across all studies, the gains and losses decision making were investigated separately, so it is unclear whether the same findings would be found when decision involve both gains and losses. This will be discussed further in the next chapter as a potential future research. Third, the predictive power of our risk measurements over real life decision has not been tested. To ensure ecological validity, participants were given remuneration corresponding to the outcome of the choices that they made. However, unlike in our decision tasks, choices are not always binary and the exact outcome probability is not always known in real life decisions. The ecological validity of the task can be tested by looking at how well risk preference can predict real life scenario risky decisions or how well choice strategy can predict the amount of choice information individual gather when making decisions.

Conclusion

In this dissertation, we investigated economic decision making in the gains and losses domains, looking specifically on how individual modulate value in response to outcome uncertainty. Gains and losses risk preferences as a measure of subjective valuation were differently altered by aging and sleep deprivation, and were consistently found to be uncorrelated across all studies. Using fMRI, overlapping areas of the value-to-utility transformation for gains and losses were found in the daMCC, which is commonly associated to executive function, but only value signal for gains were found to be encoded in the vmPFC, which is commonly associated to the valuative/affective system. The dissociable effects of different state modulations and the differences and overlaps between the gains and losses domains are the result of differential encoding and interaction between the valuative/affective system (e.g. the encoding of value signal) and the engagement of shared non-valuative processes such as executive processes (e.g. the value-to-utility transformation, the calculation of expected value). Overall, these results demonstrate the complexity of decision making – suggesting that there are both dissociable and overlapping cognitive/neural mechanisms across different domains.

Chapter 8: Future Research Direction

Many decisions involve the integration of information for both potential gains and losses. In the studies in this dissertation, although we investigated decision making in both the gains and losses domains, we looked at each domain separately. Critically, most natural decisions feature both potential gains and losses (e.g. investing in risky shares or foreign exchange), so these aspects must be integrated. However, it remains unclear whether decision making in the gains and losses domains are predictive of decision making when potential gains and potential losses coexist. Building up from our current findings, we propose a continuation study using gambles with both prospective gains and losses (mixed gambles).

The proposed future study aims at examining the core components of human decision making – the relationship between gains and losses valuation and their integration in the brain. The study builds on the significant behavioral and neural evidence (from decades of behavioral studies, our recent studies, and presented preliminary data below) that gains and losses decision making are not the result of a general-purpose machinery – our brains treat gains and losses differently. Specifically, we aim to: 1) continue our investigation for the neural encoding of value signal for losses using fMRI and 2) determine the interactions between gains and losses in the transformation from objective value to an integrated subjective utility.

Identifying the neural encoding of value signal for losses using fMRI

In Chapter 6, we showed that while there is clear encoding of value signal for gains in the vmPFC, there is no evidence of encoding of value signal for losses. We note that our study was highly powered statistically, as we had 30 participants each of whom completed 15 trials for each of the nine examined value levels in each domain. As such, this finding suggests that gains and losses are encoded differently in the brain. These results will have huge implications in our understanding of value encoding in the brain (e.g. understanding the framing effect better, understanding whether the vmPFC signal is truly a multipurpose value signal or just an approach motivation signal).

Our plan is to test whether we can still replicate the absence of value signal for losses using another risky decision task different from the one used in our previous fMRI study in Chapter 6. We will determine which brain regions encode value signal for losses and specifically look for its presence in the vmPFC. Secondly, we will also determine the neural encoding of the interaction of gains and losses values in mixed gamble – how prospective gains and losses values are integrated to form the overall representation of the gamble value by searching for areas encoding the integration of gains and losses values in mixed gambles. It may be that the vmPFC encodes the final value that incorporates both the potential gains and potential losses, but is limited to positive final values. If this is the case, the vmPFC value signal would only be found in gains gambles and mixed gambles with positive final values, but not for losses gambles or mixed gambles with negative final values. Such result would suggest that the vmPFC value signal encodes the degree of 'approach motivation' of the option instead of a multipurpose value signal (as discussed in Chapter 7).

Determining the interactions between gains and losses in the transformation from objective value to an integrated subjective utility

In Chapter 6, we also localized the information necessary to perform the value-to-utility transformation to the daMCC, with overlapping areas between the gains and losses domains. As we examined the gains and losses domains independently, it remains unknown how these signals interact/integrate when both potential gains and potential losses are introduced.

One main question we would like to answer is whether our brain is able to perform multiple value-to-utility computations simultaneously to form the overall representation of the subjective value of an object – how are gains and losses value integrated together to form the subjective value of an option? Using risky gambles, we plan to empirically test which of these possible value-to-utility mechanisms actually happens in the brain:

1) The gains and losses values are first integrated to create an overall expected value representation before the value-to-utility computation takes place (Figure 8.1A). The brain first calculates the objective expected value of the option. If the overall expected value of the option is positive (in the gains domain), the value-to-utility transformation will be performed based on gains risk preference value, otherwise, if the expected value of the option is negative (in the losses domain), the value-to-utility transformation will be performed based on losses risk preference value. In either way, only a single value-to-

utility computation is performed each time. If this is true, we would expect the gains and losses risk preferences to remain uncorrelated as found in Chapter 6 as the gains and losses value-to-utility transformation do not interact with each other.

2) The gains and losses value-to-utility transformations are performed independently one after another (but not simultaneously) and thereafter, their subjective values are integrated together (Figure 8.1B). If this is true, again we would expect the gains and losses risk preferences to remain uncorrelated as the gains and losses value-to-utility transformations still happens independently.

3) The gains and losses value-to-utility transformations are performed simultaneously but still independently and their subjective values are integrated together afterwards (Figure 8.1C). If this is the case, again we would expect the gains and losses risk preferences to remain uncorrelated as the gains and losses value-to-utility transformations still do not interact/interfere with each other.

4) The gains and losses value-to-utility transformations are performed together with interaction/interference across transformations such that the presence of multiple simultaneous value-to-utility transformations result in alterations in the value-to-utility calculations (Figure 8.1D). If this is true, we would expect to find a significant correlation between gains and losses risk preferences in mixed gambles as gains risk preferences are now influenced by losses risk preferences and vice versa. This could possibly mean that the gains and losses risk preferences merge together forming a combined risk preference, so only one transformation is performed for both gains and losses

values. If this is the case, much like there is a bottleneck in information processing for attention (we can only attend to a small number of items at a time), it may be the case that we can only perform one transformation at a time without interference across transformations.

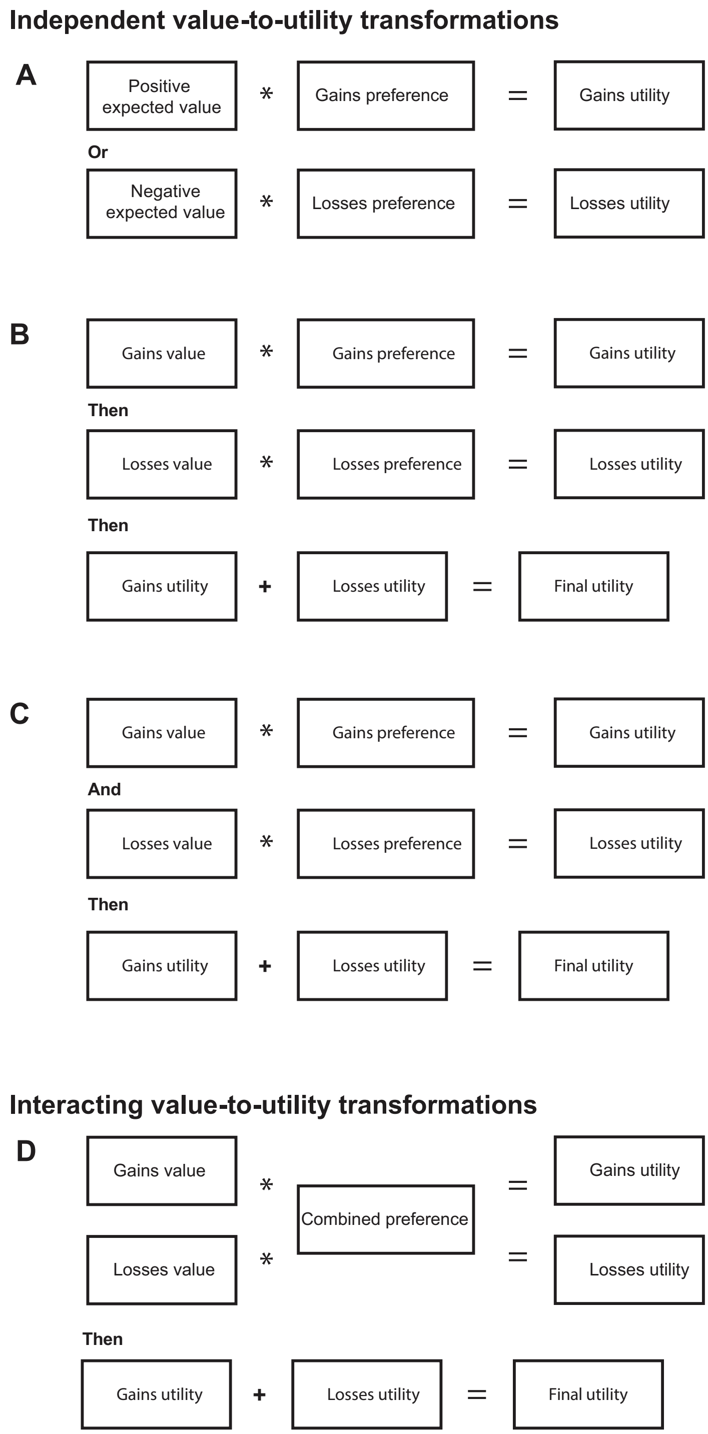

Figure 8.1. Modeling independent and interactive possible value-to-utility transformations. (A) The gains and losses values are first integrated to create

an overall expected value representation before the value-to-utility transformation takes place. (B) The gains and losses value-to-utility transformations are performed independently one after another and their utilities are integrated together afterwards. (C) The gains and losses value-to-utility transformations are performed simultaneously but still independently and their utilities are integrated together afterwards. (D) The gains and losses value-to-utility transformations are performed together with interaction/interference across transformations forming a combined risk preference value.

Task designs and potential analyses

With the aim of identifying brain regions that encode value signal and the value-to-utility transformation, we have recently developed an fMRI decision task. Additionally, we have also developed a behavioral decision task with the purpose of quantifying individuals risk preferences in the isolated gains domain, isolated losses domain and mixed domain. The task designs and potential analyses are described below.

fMRI decision task. We have developed a gamble rating task to focus on the specific cognitive processes we aim to engage and compare using fMRI which is the value encoding of isolated gains, isolated losses and intermixed gains and losses. To this end, we have removed the comparison of two options (as used in all the studies in this current dissertation), and instead present participants with a single gamble and ask them to rate it on a 4-point scale (strongly dislike, dislike, like, strongly like). Each gamble is composed of three potential components, 1) a zero outcome, 2) a positive outcome, and 3) a negative outcome, with 33.33% likelihood for each outcome (Figure 8.2). All gambles feature a zero outcome for at least 1 pie piece. Across trials, the gamble includes varying values of positive or negative outcomes (from -$18 to $18) in order to construct 4 trials types, trials that feature 1) just zeros, 2) just gains, 3) just losses, or 4) both (mixed trials). By varying the value of each option independently, we will be able to explicitly map out the independent value signals for gains only and losses only, and their intermixed resolution.

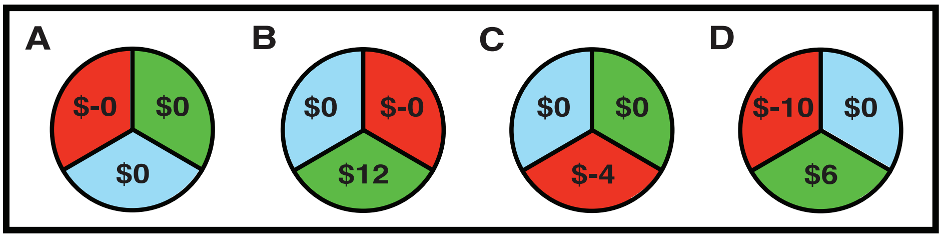

Figure 8.2. Example fMRI task trials. (A) Neutral trial, (B) gains trial, (C) losses trial, and (D) mixed trial.

Analyses of the neuroimaging data will be performed in FSL (Jenkinson et al., 2012). General Linear Model (GLM) analysis will be performed to identify regions containing neural activity of interest. We plan to create multiple models as described below (similar to the GLMs created in the fMRI study in Chapter 6) for the purpose of investigating different research questions and achieving our study aims.

1) GLM 1: Categorical trial types. This is the base model used to categorically separate trial types. Each of the four trial types will be represented by a simple box-car regressor, convolved with a double gamma hemodynamic response function. The four regressors will represent: #1 neutral trials, #2 gains trials, #3 losses trials, and #4 mixed trials. We will also include a nuisance regressor, #5 button press. This model will be used to identify the main effects of trials types and contrasts between trial types.

2) GLM 2: Separated gains and losses values. This model will include all the regressors in the base model (regressor #1-5), with the addition of 4

parametric regressors modeling trial values during the decision period: #6 gains values in gains trials, #7 losses values in losses trials, #8 gains values in mixed trials, and #9 losses values in mixed trials.

3) GLM 3: Combined gains and losses values in mixed trials. This model is similar to GLM 2, but instead of having two parametric value regressors for the mixed trial, we will only have one regressor, which is the difference between the gains value and losses values in the mixed trials. This model will include all the regressors in the base model (regressor #1-5), with the addition of 3 parametric regressors modeling trial values during the decision period: #6 gains values in gains trials, #7 losses values in losses trials, #8 difference between gains and losses values in mixed trials.

4) GLM 4: Categorical examination of value levels. This model is designed to extract the actual neural encoding of the gains and losses value signals. This model will include all the regressors in the base model (regressor #1-5), with the addition of 19 box-car task regressors (2 domains x 9 value levels and one for neutral trial).

By conducting whole brain analyses using these GLMs, we will be able to: 1) determine what brain areas encode gains value signal in gains trials (GLM 2 regressor #6; replicating prior studies) and in mixed trials (GLM 2 regressor #8), 2) determine what brain areas encode losses value signal in losses trials (GLM 2 regressor #7) and in mixed trials (GLM 2 regressor #8), and 3) determine the neural encoding of the interaction of gains and losses values in mixed gamble (GLM 2 regressor #7). By conducting region-of-interest (ROI) analysis, we will be able to specifically test the presence of losses value signal in the vmPFC by extracting the beta values of the 9 losses value level regressors (GLM 4) from the vmPFC. We could also perform ROI analyses in the nucleus accumbens and amygdala.

In addition, Support Vector Machine (SVM) analyses will be performed to test for non-linear encoding of gains and losses value signals. These analyses will be limited to comparison of two categories. We plan to compare neural encoding of 'dislike' and 'strongly dislike' responses and of 'like' and 'strongly like' responses separately for gains and losses trials.

Behavioral decision task. We have developed a gamble rating task to quantify risk preferences in the isolated gains domain, isolated losses domain, and mixed domain. These risk preferences will be used as covariates in our fMRI analyses to identify the interaction between gains and losses value-to-utility transformations. We created mixed gambles composing of three parts, with each part having either a 25%, 33.33%, 50%, 66.67% or 75% probability (for a sum of 100% in each gamble). These three parts are either 1) a prospective gain, 2) a prospective loss, or 3) zero (Figure 8.3). Gambles were again constructed to have specific expected values and were intermixed together with isolated (pure) domain trials. We will compute risk preferences for pure gains, pure losses, mixed gains and mixed losses independently using a power function metric as used in our previous studies (see Chapter 5 and 6).

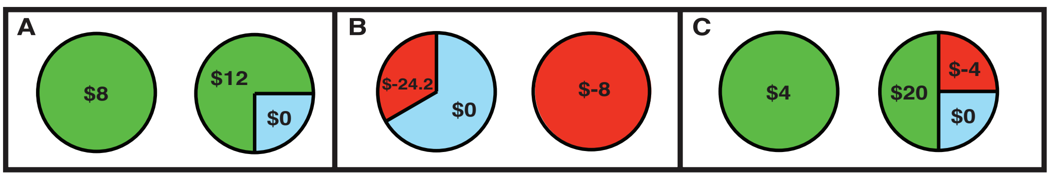

Figure 8.3. Example of behavioral task trials. (A) presents a trial with prospective gains, (B) presents a trial with prospective losses, and (C) shows trial with both prospective gains and losses.

Preliminary Results

We have begun collection of preliminary behavioral data using this newly modified version of our behavioral decision task that includes mixed gambles. We collected data from 60 participants (29 males; mean ± SD age = 22.30 ± 1.97 years). We quantified their gains and losses risk preferences in the mixed domain and identified the interrelationships between isolated (pure) domain and mixed domain risk preferences using the previously used power function metric to empirically test the possible mechanisms previously mentioned (see Figure 8.1). First, we tested the correlation between gains and losses risk preferences to see whether we could replicate our prior studies. We found absence of correlations between gains and losses risk preferences for the isolated trials (trials with only gains or only losses components) ($r(58) = .14$, $p = .28$). We also tested the relationship between isolated and mixed trials within each domain and found strong correlations (gains: $r(37) = .69$, $p < .0001$; losses: $r(52) = .56$, $p < .0001$). Next we tested the correlation between gains and losses risk preferences in mixed trials – the crucial test. If these risk preferences were the results of independent processes, we would expect to find that the absence of correlation maintained in the mixed trials as found between the gains and losses isolated trials. Instead, we found a very strong correlation between mixed gains and mixed losses risk preferences ($r(31) = .70$, $p < .0001$; correlation significantly different from cross-domain pure risk preferences correlation: $z = 4.47$, $p < .0001$) (Figure 8.4). This provides evidence that the presence of multiple simultaneous value-to-utility computations (for gains value and losses value), results in alterations of the calculations. This suggests evidence for a neural bottleneck in the value-to-utility computation where we can only perform one transformation at a time without interference across transformations.

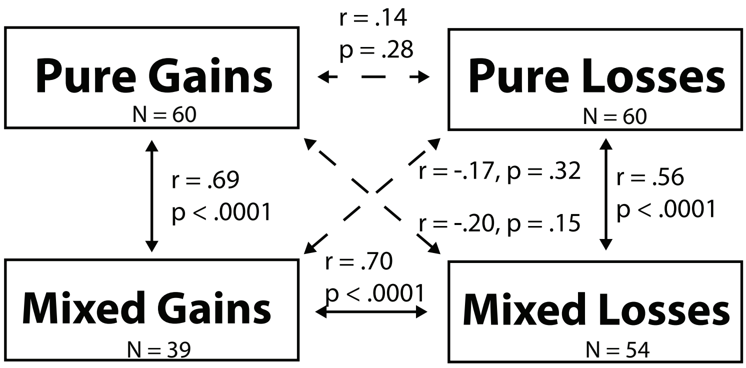

Figure 8.4. Relationships between gain and loss preferences between isolated (pure) and mixed trial types. Critically, there is an absence of correlation between pure gains and losses, but a strong correlation when they appear simultaneously as mixed gains and mixed losses.

Further Analyses

Our next step is to perform a neural examination of the bottleneck in the value-to-utility transformation using fMRI. This component will utilize the data from the fMRI decision task described above and also the risk preferences obtained from the behavioral decision task. All participants will perform the behavioral task before they enter the scanner, such that we will be able to integrate their expressed risk preferences for gains and losses into the calculation of the separable and combined valuation signals.

Analyses of the neuroimaging data will also be performed in FSL (Jenkinson et al., 2012). We will construct GLMs with individual's risk preference values as a between-subject covariate to identify brain regions that encode a linear value signal whose slope varies across individuals as a function of the specific value-to-utility transformation that they are performing – an analysis that we developed previously (Chapter 6). We will perform this analysis separately for pure gains, pure losses, mixed gains and mixed losses risk preferences. Based on our previous study, we expect to find this pattern of activation within the daMCC, overlapping across domains. We will be able to test whether the daMCC still encodes the pure gains risk preference and pure losses risk preference independently (perhaps multiplexing the signal) during mixed trials, or if the system now reflects a single value-to-utility transformation that is intermediate between the two isolated preferences. Critically, this will allow us to differentiate whether the interaction is occurring at the value-to-utility stage or at a later stage of the decision process.

Functional connectivity analyses will allow us to identify the neural system that is involved in the value-to-utility transformation for each trial type. Previously, in Chapter 6, while investigating gains and losses separately, we found that the daMCC ROI was positively connected with the dlPFC/IFG and negatively functionally connected with the NAcc.

Implications

The importance of these findings should not be understated. While it is theoretically possible that our decision making processes can handle gains and losses processing independently (e.g. existing studies on framing effect that only look at pure domain decisions have shown that people respond differently for gains and losses), these results indicate that composite decisions may result in interactions in the information processing. Such interactions will inevitably result in poorer quality decision making when compared to independent processing of each dimension's information. If this is true, the proof of the existence of this bottleneck will result in a simple strategy to avoid these maladaptive decisions – a strategy of treating each component in a serial process.

Overall, this proposed future project will extend current understanding about the neural mechanisms of decision making by looking at how gains and losses interactions are represented in the brain. As mentioned earlier, many of our real life risky decisions involve both potential gains and losses. Unfortunately, no study has investigated the neural mechanisms of how gains and losses value-to-utility transformations are integrated. This research will provide an insight of the neural mechanisms involved in the clear behavioral differences that occur between gains and losses decision making (such as framing and loss aversion).

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Appendix A. Gains and Losses Tasks used in Chapter 2, 3 and 4.

Gains Risky Trials				
Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
1	3	0.25	6	0.5
2	3	0.5	3	0.5
3	3	0.75	2	0.5
4	3	0.25	12	1
5	3	0.5	6	1
6	3	0.75	4	1
7	3	0.25	15.6	1.3
8	3	0.5	7.8	1.3
9	3	0.75	5.2	1.3
10	3	0.25	19.2	1.6
11	3	0.5	9.6	1.6
12	3	0.75	6.4	1.6
13	3	0.25	22.8	1.9
14	3	0.5	11.4	1.9
15	3	0.75	7.6	1.9
16	3	0.25	26.4	2.2
17	3	0.5	13.2	2.2
18	3	0.75	8.8	2.2
19	3	0.25	30	2.5
20	3	0.5	15	2.5
21	3	0.75	10	2.5
22	3	0.25	36	3
23	3	0.5	18	3
24	3	0.75	12	3
25	3	0.25	42	3.5
26	3	0.5	21	3.5
27	3	0.75	14	3.5
28	4	0.25	8	0.5
29	4	0.5	4	0.5
30	4	0.75	2.7	0.5
31	4	0.25	16	1
32	4	0.5	8	1
33	4	0.75	5.3	1
34	4	0.25	20.8	1.3
35	4	0.5	10.4	1.3
36	4	0.75	6.9	1.3
37	4	0.25	25.6	1.6
38	4	0.5	12.8	1.6
39	4	0.75	8.5	1.6
40	4	0.25	30.4	1.9

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
41	4	0.5	15.2	1.9
42	4	0.75	10.1	1.9
43	4	0.25	35.2	2.2
44	4	0.5	17.6	2.2
45	4	0.75	11.7	2.2
46	4	0.25	40	2.5
47	4	0.5	20	2.5
48	4	0.75	13.3	2.5
49	4	0.25	48	3
50	4	0.5	24	3
51	4	0.75	16	3
52	4	0.25	56	3.5
53	4	0.5	28	3.5
54	4	0.75	18.7	3.5
55	5	0.25	10	0.5
56	5	0.5	5	0.5
57	5	0.75	3.3	0.5
58	5	0.25	20	1
59	5	0.5	10	1
60	5	0.75	6.7	1
61	5	0.25	26	1.3
62	5	0.5	13	1.3
63	5	0.75	8.7	1.3
64	5	0.25	32	1.6
65	5	0.5	16	1.6
66	5	0.75	10.7	1.6
67	5	0.25	38	1.9
68	5	0.5	19	1.9
69	5	0.75	12.7	1.9
70	5	0.25	44	2.2
71	5	0.5	22	2.2
72	5	0.75	14.7	2.2
73	5	0.25	50	2.5
74	5	0.5	25	2.5
75	5	0.75	16.7	2.5
76	5	0.25	60	3
77	5	0.5	30	3
78	5	0.75	20	3
79	5	0.25	70	3.5
80	5	0.5	35	3.5
81	5	0.75	23.3	3.5
82	6	0.25	12	0.5
83	6	0.5	6	0.5

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
84	6	0.75	4	0.5
85	6	0.25	24	1
86	6	0.5	12	1
87	6	0.75	8	1
88	6	0.25	31.2	1.3
89	6	0.5	15.6	1.3
90	6	0.75	10.4	1.3
91	6	0.25	38.4	1.6
92	6	0.5	19.2	1.6
93	6	0.75	12.8	1.6
94	6	0.25	45.6	1.9
95	6	0.5	22.8	1.9
96	6	0.75	15.2	1.9
97	6	0.25	52.8	2.2
98	6	0.5	26.4	2.2
99	6	0.75	17.6	2.2
100	6	0.25	60	2.5
101	6	0.5	30	2.5
102	6	0.75	20	2.5
103	6	0.25	72	3
104	6	0.5	36	3
105	6	0.75	24	3
106	6	0.25	84	3.5
107	6	0.5	42	3.5
108	6	0.75	28	3.5
109	7	0.25	14	0.5
110	7	0.5	7	0.5
111	7	0.75	4.7	0.5
112	7	0.25	28	1
113	7	0.5	14	1
114	7	0.75	9.3	1
115	7	0.25	36.4	1.3
116	7	0.5	18.2	1.3
117	7	0.75	12.1	1.3
118	7	0.25	44.8	1.6
119	7	0.5	22.4	1.6
120	7	0.75	14.9	1.6
121	7	0.25	53.2	1.9
122	7	0.5	26.6	1.9
123	7	0.75	17.7	1.9
124	7	0.25	61.6	2.2
125	7	0.5	30.8	2.2
126	7	0.75	20.5	2.2

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
127	7	0.25	70	2.5
128	7	0.5	35	2.5
129	7	0.75	23.3	2.5
130	7	0.25	84	3
131	7	0.5	42	3
132	7	0.75	28	3
133	7	0.25	98	3.5
134	7	0.5	49	3.5
135	7	0.75	32.7	3.5
Gains Ambiguity Trials				
Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
1	3		3	0.5
2	3		6	1
3	3		12	2
4	3		18	3
5	3		24	4
6	3		36	6
7	4		4	0.5
8	4		8	1
9	4		16	2
10	4		24	3
11	4		32	4
12	4		48	6
13	5		5	0.5
14	5		10	1
15	5		20	2
16	5		30	3
17	5		40	4
18	5		60	6
19	6		6	0.5
20	6		12	1
21	6		24	2
22	6		36	3
23	6		48	4
24	6		72	6
25	7		7	0.5
26	7		14	1
27	7		28	2
28	7		42	3
29	7		56	4
30	7		84	6

Losses Risk Trials				
Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
1	-3	0.25	-1.2	0.1
2	-3	0.5	-0.6	0.1
3	-3	0.75	-0.4	0.1
4	-3	0.25	-3.6	0.3
5	-3	0.5	-1.8	0.3
6	-3	0.75	-1.2	0.3
7	-3	0.25	-6	0.5
8	-3	0.5	-3	0.5
9	-3	0.75	-2	0.5
10	-3	0.25	-9.6	0.8
11	-3	0.5	-4.8	0.8
12	-3	0.75	-3.2	0.8
13	-3	0.25	-12	1
14	-3	0.5	-6	1
15	-3	0.75	-4	1
16	-3	0.25	-15.6	1.3
17	-3	0.5	-7.8	1.3
18	-3	0.75	-5.2	1.3
19	-3	0.25	-18	1.5
20	-3	0.5	-9	1.5
21	-3	0.75	-6	1.5
22	-3	0.25	-24	2
23	-3	0.5	-12	2
24	-3	0.75	-8	2
25	-3	0.25	-36	3
26	-3	0.5	-18	3
27	-3	0.75	-12	3
28	-3	0.25	-48	4
29	-3	0.5	-24	4
30	-3	0.75	-16	4
31	-4	0.25	-1.6	0.1
32	-4	0.5	-0.8	0.1
33	-4	0.75	-0.5	0.1
34	-4	0.25	-4.8	0.3
35	-4	0.5	-2.4	0.3
36	-4	0.75	-1.6	0.3
37	-4	0.25	-8	0.5
38	-4	0.5	-4	0.5
39	-4	0.75	-2.7	0.5
40	-4	0.25	-12.8	0.8
41	-4	0.5	-6.4	0.8
42	-4	0.75	-4.3	0.8

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
43	-4	0.25	-16	1
44	-4	0.5	-8	1
45	-4	0.75	-5.3	1
46	-4	0.25	-20.8	1.3
47	-4	0.5	-10.4	1.3
48	-4	0.75	-6.9	1.3
49	-4	0.25	-24	1.5
50	-4	0.5	-12	1.5
51	-4	0.75	-8	1.5
52	-4	0.25	-32	2
53	-4	0.5	-16	2
54	-4	0.75	-10.7	2
55	-4	0.25	-48	3
56	-4	0.5	-24	3
57	-4	0.75	-16	3
58	-4	0.25	-64	4
59	-4	0.5	-32	4
60	-4	0.75	-21.3	4
61	-5	0.25	-2	0.1
62	-5	0.5	-1	0.1
63	-5	0.75	-0.7	0.1
64	-5	0.25	-6	0.3
65	-5	0.5	-3	0.3
66	-5	0.75	-2	0.3
67	-5	0.25	-10	0.5
68	-5	0.5	-5	0.5
69	-5	0.75	-3.3	0.5
70	-5	0.25	-16	0.8
71	-5	0.5	-8	0.8
72	-5	0.75	-5.3	0.8
73	-5	0.25	-20	1
74	-5	0.5	-10	1
75	-5	0.75	-6.7	1
76	-5	0.25	-26	1.3
77	-5	0.5	-13	1.3
78	-5	0.75	-8.7	1.3
79	-5	0.25	-30	1.5
80	-5	0.5	-15	1.5
81	-5	0.75	-10	1.5
82	-5	0.25	-40	2
83	-5	0.5	-20	2
84	-5	0.75	-13.3	2
85	-5	0.25	-60	3

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
86	-5	0.5	-30	3
87	-5	0.75	-20	3
88	-5	0.25	-80	4
89	-5	0.5	-40	4
90	-5	0.75	-26.7	4
91	-6	0.25	-2.4	0.1
92	-6	0.5	-1.2	0.1
93	-6	0.75	-0.8	0.1
94	-6	0.25	-7.2	0.3
95	-6	0.5	-3.6	0.3
96	-6	0.75	-2.4	0.3
97	-6	0.25	-12	0.5
98	-6	0.5	-6	0.5
99	-6	0.75	-4	0.5
100	-6	0.25	-19.2	0.8
101	-6	0.5	-9.6	0.8
102	-6	0.75	-6.4	0.8
103	-6	0.25	-24	1
104	-6	0.5	-12	1
105	-6	0.75	-8	1
106	-6	0.25	-31.2	1.3
107	-6	0.5	-15.6	1.3
108	-6	0.75	-10.4	1.3
109	-6	0.25	-36	1.5
110	-6	0.5	-18	1.5
111	-6	0.75	-12	1.5
112	-6	0.25	-48	2
113	-6	0.5	-24	2
114	-6	0.75	-16	2
115	-6	0.25	-72	3
116	-6	0.5	-36	3
117	-6	0.75	-24	3
118	-6	0.25	-96	4
119	-6	0.5	-48	4
120	-6	0.75	-32	4
121	-7	0.25	-2.8	0.1
122	-7	0.5	-1.4	0.1
123	-7	0.75	-0.9	0.1
124	-7	0.25	-8.4	0.3
125	-7	0.5	-4.2	0.3
126	-7	0.75	-2.8	0.3
127	-7	0.25	-14	0.5
128	-7	0.5	-7	0.5

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
129	-7	0.75	-4.7	0.5
130	-7	0.25	-22.4	0.8
131	-7	0.5	-11.2	0.8
132	-7	0.75	-7.5	0.8
133	-7	0.25	-28	1
134	-7	0.5	-14	1
135	-7	0.75	-9.3	1
136	-7	0.25	-36.4	1.3
137	-7	0.5	-18.2	1.3
138	-7	0.75	-12.1	1.3
139	-7	0.25	-42	1.5
140	-7	0.5	-21	1.5
141	-7	0.75	-14	1.5
142	-7	0.25	-56	2
143	-7	0.5	-28	2
144	-7	0.75	-18.7	2
145	-7	0.25	-84	3
146	-7	0.5	-42	3
147	-7	0.75	-28	3
148	-7	0.25	-112	4
149	-7	0.5	-56	4
150	-7	0.75	-37.3	4
Losses Ambiguity Trials				
Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
1	-3		-0.6	0.1
2	-3		-1.8	0.3
3	-3		-3	0.5
4	-3		-4.8	0.8
5	-3		-6	1
6	-3		-7.8	1.3
7	-3		-9	1.5
8	-3		-12	2
9	-3		-18	3
10	-3		-24	4
11	-4		-0.8	0.1
12	-4		-2.4	0.3
13	-4		-4	0.5
14	-4		-6.4	0.8
15	-4		-8	1
16	-4		-10.4	1.3
17	-4		-12	1.5

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
18	-4		-16	2
19	-4		-24	3
20	-4		-32	4
21	-5		-1	0.1
22	-5		-3	0.3
23	-5		-5	0.5
24	-5		-8	0.8
25	-5		-10	1
26	-5		-13	1.3
27	-5		-15	1.5
28	-5		-20	2
29	-5		-30	3
30	-5		-40	4
31	-6		-1.2	0.1
32	-6		-3.6	0.3
33	-6		-6	0.5
34	-6		-9.6	0.8
35	-6		-12	1
36	-6		-15.6	1.3
37	-6		-18	1.5
38	-6		-24	2
39	-6		-36	3
40	-6		-48	4
41	-7		-1.4	0.1
42	-7		-4.2	0.3
43	-7		-7	0.5
44	-7		-11.2	0.8
45	-7		-14	1
46	-7		-18.2	1.3
47	-7		-21	1.5
48	-7		-28	2
49	-7		-42	3
50	-7		-56	4

Appendix B. Gains and Losses Task used in Chapter 5.

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
1	3	0.25	3.0	0.25
2	3	0.5	1.5	0.25
3	3	0.75	1.0	0.25
4	3	0.25	4.0	0.33
5	3	0.5	2.0	0.33
6	3	0.75	1.3	0.33
7	3	0.25	6.0	0.5
8	3	0.5	3.0	0.5
9	3	0.75	2.0	0.5
10	3	0.25	7.9	0.66
11	3	0.5	4.0	0.66
12	3	0.75	2.6	0.66
13	3	0.25	9.6	0.8
14	3	0.5	4.8	0.8
15	3	0.75	3.2	0.8
16	3	0.25	12.0	1
17	3	0.5	6.0	1
18	3	0.75	4.0	1
19	3	0.25	15.0	1.25
20	3	0.5	7.5	1.25
21	3	0.75	5.0	1.25
22	3	0.25	18.0	1.5
23	3	0.5	9.0	1.5
24	3	0.75	6.0	1.5
25	3	0.25	24.0	2
26	3	0.5	12.0	2
27	3	0.75	8.0	2
28	3	0.25	36.0	3
29	3	0.5	18.0	3
30	3	0.75	12.0	3
31	3	0.25	48.0	4
32	3	0.5	24.0	4
33	3	0.75	16.0	4
34	4	0.25	4.0	0.25
35	4	0.5	2.0	0.25
36	4	0.75	1.3	0.25
37	4	0.25	5.3	0.33
38	4	0.5	2.6	0.33
39	4	0.75	1.8	0.33
40	4	0.25	8.0	0.5

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
41	4	0.5	4.0	0.5
42	4	0.75	2.7	0.5
43	4	0.25	10.6	0.66
44	4	0.5	5.3	0.66
45	4	0.75	3.5	0.66
46	4	0.25	12.8	0.8
47	4	0.5	6.4	0.8
48	4	0.75	4.3	0.8
49	4	0.25	16.0	1
50	4	0.5	8.0	1
51	4	0.75	5.3	1
52	4	0.25	20.0	1.25
53	4	0.5	10.0	1.25
54	4	0.75	6.7	1.25
55	4	0.25	24.0	1.5
56	4	0.5	12.0	1.5
57	4	0.75	8.0	1.5
58	4	0.25	32.0	2
59	4	0.5	16.0	2
60	4	0.75	10.7	2
61	4	0.25	48.0	3
62	4	0.5	24.0	3
63	4	0.75	16.0	3
64	4	0.25	64.0	4
65	4	0.5	32.0	4
66	4	0.75	21.3	4
67	5	0.25	5.0	0.25
68	5	0.5	2.5	0.25
69	5	0.75	1.7	0.25
70	5	0.25	6.6	0.33
71	5	0.5	3.3	0.33
72	5	0.75	2.2	0.33
73	5	0.25	10.0	0.5
74	5	0.5	5.0	0.5
75	5	0.75	3.3	0.5
76	5	0.25	13.2	0.66
77	5	0.5	6.6	0.66
78	5	0.75	4.4	0.66
79	5	0.25	16.0	0.8
80	5	0.5	8.0	0.8
81	5	0.75	5.3	0.8
82	5	0.25	20.0	1
83	5	0.5	10.0	1

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
84	5	0.75	6.7	1
85	5	0.25	25.0	1.25
86	5	0.5	12.5	1.25
87	5	0.75	8.3	1.25
88	5	0.25	30.0	1.5
89	5	0.5	15.0	1.5
90	5	0.75	10.0	1.5
91	5	0.25	40.0	2
92	5	0.5	20.0	2
93	5	0.75	13.3	2
94	5	0.25	60.0	3
95	5	0.5	30.0	3
96	5	0.75	20.0	3
97	5	0.25	80.0	4
98	5	0.5	40.0	4
99	5	0.75	26.7	4
100	6	0.25	6.0	0.25
101	6	0.5	3.0	0.25
102	6	0.75	2.0	0.25
103	6	0.25	7.9	0.33
104	6	0.5	4.0	0.33
105	6	0.75	2.6	0.33
106	6	0.25	12.0	0.5
107	6	0.5	6.0	0.5
108	6	0.75	4.0	0.5
109	6	0.25	15.8	0.66
110	6	0.5	7.9	0.66
111	6	0.75	5.3	0.66
112	6	0.25	19.2	0.8
113	6	0.5	9.6	0.8
114	6	0.75	6.4	0.8
115	6	0.25	24.0	1
116	6	0.5	12.0	1
117	6	0.75	8.0	1
118	6	0.25	30.0	1.25
119	6	0.5	15.0	1.25
120	6	0.75	10.0	1.25
121	6	0.25	36.0	1.5
122	6	0.5	18.0	1.5
123	6	0.75	12.0	1.5
124	6	0.25	48.0	2
125	6	0.5	24.0	2
126	6	0.75	16.0	2

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
127	6	0.25	72.0	3
128	6	0.5	36.0	3
129	6	0.75	24.0	3
130	6	0.25	96.0	4
131	6	0.5	48.0	4
132	6	0.75	32.0	4
133	7	0.25	7.0	0.25
134	7	0.5	3.5	0.25
135	7	0.75	2.3	0.25
136	7	0.25	9.2	0.33
137	7	0.5	4.6	0.33
138	7	0.75	3.1	0.33
139	7	0.25	14.0	0.5
140	7	0.5	7.0	0.5
141	7	0.75	4.7	0.5
142	7	0.25	18.5	0.66
143	7	0.5	9.2	0.66
144	7	0.75	6.2	0.66
145	7	0.25	22.4	0.8
146	7	0.5	11.2	0.8
147	7	0.75	7.5	0.8
148	7	0.25	28.0	1
149	7	0.5	14.0	1
150	7	0.75	9.3	1
151	7	0.25	35.0	1.25
152	7	0.5	17.5	1.25
153	7	0.75	11.7	1.25
154	7	0.25	42.0	1.5
155	7	0.5	21.0	1.5
156	7	0.75	14.0	1.5
157	7	0.25	56.0	2
158	7	0.5	28.0	2
159	7	0.75	18.7	2
160	7	0.25	84.0	3
161	7	0.5	42.0	3
162	7	0.75	28.0	3
163	7	0.25	112.0	4
164	7	0.5	56.0	4
165	7	0.75	37.3	4
166	-3	0.25	-12.0	4
167	-3	0.5	-12.0	4
168	-3	0.75	-12.0	4
169	-3	0.25	-9.0	3

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
170	-3	0.5	-9.0	3
171	-3	0.75	-9.0	3
172	-3	0.25	-6.0	2
173	-3	0.5	-6.0	2
174	-3	0.75	-6.0	2
175	-3	0.25	-4.5	1.5
176	-3	0.5	-4.5	1.5
177	-3	0.75	-4.5	1.5
178	-3	0.25	-3.8	1.25
179	-3	0.5	-3.8	1.25
180	-3	0.75	-3.8	1.25
181	-3	0.25	-3.0	1
182	-3	0.5	-3.0	1
183	-3	0.75	-3.0	1
184	-3	0.25	-2.4	0.8
185	-3	0.5	-2.4	0.8
186	-3	0.75	-2.4	0.8
187	-3	0.25	-2.0	0.66
188	-3	0.5	-2.0	0.66
189	-3	0.75	-2.0	0.66
190	-3	0.25	-1.5	0.5
191	-3	0.5	-1.5	0.5
192	-3	0.75	-1.5	0.5
193	-3	0.25	-1.0	0.33
194	-3	0.5	-1.0	0.33
195	-3	0.75	-1.0	0.33
196	-3	0.25	-0.8	0.25
197	-3	0.5	-0.8	0.25
198	-3	0.75	-0.8	0.25
199	-4	0.25	-16.0	4
200	-4	0.5	-16.0	4
201	-4	0.75	-16.0	4
202	-4	0.25	-12.0	3
203	-4	0.5	-12.0	3
204	-4	0.75	-12.0	3
205	-4	0.25	-8.0	2
206	-4	0.5	-8.0	2
207	-4	0.75	-8.0	2
208	-4	0.25	-6.0	1.5
209	-4	0.5	-6.0	1.5
210	-4	0.75	-6.0	1.5
211	-4	0.25	-5.0	1.25
212	-4	0.5	-5.0	1.25

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
213	-4	0.75	-5.0	1.25
214	-4	0.25	-4.0	1
215	-4	0.5	-4.0	1
216	-4	0.75	-4.0	1
217	-4	0.25	-3.2	0.8
218	-4	0.5	-3.2	0.8
219	-4	0.75	-3.2	0.8
220	-4	0.25	-2.6	0.66
221	-4	0.5	-2.6	0.66
222	-4	0.75	-2.6	0.66
223	-4	0.25	-2.0	0.5
224	-4	0.5	-2.0	0.5
225	-4	0.75	-2.0	0.5
226	-4	0.25	-1.3	0.33
227	-4	0.5	-1.3	0.33
228	-4	0.75	-1.3	0.33
229	-4	0.25	-1.0	0.25
230	-4	0.5	-1.0	0.25
231	-4	0.75	-1.0	0.25
232	-5	0.25	-20.0	4
233	-5	0.5	-20.0	4
234	-5	0.75	-20.0	4
235	-5	0.25	-15.0	3
236	-5	0.5	-15.0	3
237	-5	0.75	-15.0	3
238	-5	0.25	-10.0	2
239	-5	0.5	-10.0	2
240	-5	0.75	-10.0	2
241	-5	0.25	-7.5	1.5
242	-5	0.5	-7.5	1.5
243	-5	0.75	-7.5	1.5
244	-5	0.25	-6.3	1.25
245	-5	0.5	-6.3	1.25
246	-5	0.75	-6.2	1.25
247	-5	0.25	-5.0	1
248	-5	0.5	-5.0	1
249	-5	0.75	-5.0	1
250	-5	0.25	-4.0	0.8
251	-5	0.5	-4.0	0.8
252	-5	0.75	-4.0	0.8
253	-5	0.25	-3.3	0.66
254	-5	0.5	-3.3	0.66
255	-5	0.75	-3.3	0.66

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
256	-5	0.25	-2.5	0.5
257	-5	0.5	-2.5	0.5
258	-5	0.75	-2.5	0.5
259	-5	0.25	-1.7	0.33
260	-5	0.5	-1.7	0.33
261	-5	0.75	-1.7	0.33
262	-5	0.25	-1.3	0.25
263	-5	0.5	-1.3	0.25
264	-5	0.75	-1.3	0.25
265	-6	0.25	-24.0	4
266	-6	0.5	-24.0	4
267	-6	0.75	-24.0	4
268	-6	0.25	-18.0	3
269	-6	0.5	-18.0	3
270	-6	0.75	-18.0	3
271	-6	0.25	-12.0	2
272	-6	0.5	-12.0	2
273	-6	0.75	-12.0	2
274	-6	0.25	-9.0	1.5
275	-6	0.5	-9.0	1.5
276	-6	0.75	-9.0	1.5
277	-6	0.25	-7.5	1.25
278	-6	0.5	-7.5	1.25
279	-6	0.75	-7.5	1.25
280	-6	0.25	-6.0	1
281	-6	0.5	-6.0	1
282	-6	0.75	-6.0	1
283	-6	0.25	-4.8	0.8
284	-6	0.5	-4.8	0.8
285	-6	0.75	-4.8	0.8
286	-6	0.25	-4.0	0.66
287	-6	0.5	-4.0	0.66
288	-6	0.75	-4.0	0.66
289	-6	0.25	-3.0	0.5
290	-6	0.5	-3.0	0.5
291	-6	0.75	-3.0	0.5
292	-6	0.25	-2.0	0.33
293	-6	0.5	-2.0	0.33
294	-6	0.75	-2.0	0.33
295	-6	0.25	-1.5	0.25
296	-6	0.5	-1.5	0.25
297	-6	0.75	-1.5	0.25
298	-7	0.25	-28.0	4

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
299	-7	0.5	-28.0	4
300	-7	0.75	-28.0	4
301	-7	0.25	-21.0	3
302	-7	0.5	-21.0	3
303	-7	0.75	-21.0	3
304	-7	0.25	-14.0	2
305	-7	0.5	-14.0	2
306	-7	0.75	-14.0	2
307	-7	0.25	-10.5	1.5
308	-7	0.5	-10.5	1.5
309	-7	0.75	-10.5	1.5
310	-7	0.25	-8.8	1.25
311	-7	0.5	-8.8	1.25
312	-7	0.75	-8.8	1.25
313	-7	0.25	-7.0	1
314	-7	0.5	-7.0	1
315	-7	0.75	-7.0	1
316	-7	0.25	-5.6	0.8
317	-7	0.5	-5.6	0.8
318	-7	0.75	-5.6	0.8
319	-7	0.25	-4.6	0.66
320	-7	0.5	-4.6	0.66
321	-7	0.75	-4.6	0.66
322	-7	0.25	-3.5	0.5
323	-7	0.5	-3.5	0.5
324	-7	0.75	-3.5	0.5
325	-7	0.25	-2.3	0.33
326	-7	0.5	-2.3	0.33
327	-7	0.75	-2.3	0.33
328	-7	0.25	-1.8	0.25
329	-7	0.5	-1.8	0.25
330	-7	0.75	-1.7	0.25

Appendix C. Gains and Losses fMRI Task used in Chapter 6.

Gains Risky Trials				
Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
1	3	0.25	3	0.25
2	3	0.5	1.5	0.25
3	3	0.75	1	0.25
4	4	0.25	4	0.25
5	4	0.5	2	0.25
6	4	0.75	1.3	0.25
7	5	0.25	5	0.25
8	5	0.5	2.5	0.25
9	5	0.75	1.7	0.25
10	6	0.25	6	0.25
11	6	0.5	3	0.25
12	6	0.75	2	0.25
13	7	0.25	7	0.25
14	7	0.5	3.5	0.25
15	7	0.75	2.3	0.25
16	3	0.25	6	0.5
17	3	0.5	3	0.5
18	3	0.75	2	0.5
19	4	0.25	8	0.5
20	4	0.5	4	0.5
21	4	0.75	2.7	0.5
22	5	0.25	10	0.5
23	5	0.5	5	0.5
24	5	0.75	3.3	0.5
25	6	0.25	12	0.5
26	6	0.5	6	0.5
27	6	0.75	4	0.5
28	7	0.25	14	0.5
29	7	0.5	7	0.5
30	7	0.75	4.7	0.5
31	3	0.25	7.9	0.66
32	3	0.5	4	0.66
33	3	0.75	2.6	0.66
34	4	0.25	10.6	0.66
35	4	0.5	5.3	0.66
36	4	0.75	3.5	0.66
37	5	0.25	13.2	0.66
38	5	0.5	6.6	0.66
39	5	0.75	4.4	0.66

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
40	6	0.25	15.8	0.66
41	6	0.5	7.9	0.66
42	6	0.75	5.3	0.66
43	7	0.25	18.5	0.66
44	7	0.5	9.2	0.66
45	7	0.75	6.2	0.66
46	3	0.25	9.6	0.8
47	3	0.5	4.8	0.8
48	3	0.75	3.2	0.8
49	4	0.25	12.8	0.8
50	4	0.5	6.4	0.8
51	4	0.75	4.3	0.8
52	5	0.25	16	0.8
53	5	0.5	8	0.8
54	5	0.75	5.3	0.8
55	6	0.25	19.2	0.8
56	6	0.5	9.6	0.8
57	6	0.75	6.4	0.8
58	7	0.25	22.4	0.8
59	7	0.5	11.2	0.8
60	7	0.75	7.5	0.8
61	3	0.25	12	1
62	3	0.5	6	1
63	3	0.75	4	1
64	4	0.25	16	1
65	4	0.5	8	1
66	4	0.75	5.3	1
67	5	0.25	20	1
68	5	0.5	10	1
69	5	0.75	6.7	1
70	6	0.25	24	1
71	6	0.5	12	1
72	6	0.75	8	1
73	7	0.25	28	1
74	7	0.5	14	1
75	7	0.75	9.3	1
76	3	0.25	15	1.25
77	3	0.5	7.5	1.25
78	3	0.75	5	1.25
79	4	0.25	20	1.25
80	4	0.5	10	1.25
81	4	0.75	6.7	1.25
82	5	0.25	25	1.25

83	5	0.5	12.5	1.25
84	5	0.75	8.3	1.25
85	6	0.25	30	1.25
86	6	0.5	15	1.25
87	6	0.75	10	1.25
88	7	0.25	35	1.25
89	7	0.5	17.5	1.25
90	7	0.75	11.7	1.25
91	3	0.25	18	1.5
92	3	0.5	9	1.5
93	3	0.75	6	1.5
94	4	0.25	24	1.5
95	4	0.5	12	1.5
96	4	0.75	8	1.5
97	5	0.25	30	1.5
98	5	0.5	15	1.5
99	5	0.75	10	1.5
100	6	0.25	36	1.5
101	6	0.5	18	1.5
102	6	0.75	12	1.5
103	7	0.25	42	1.5
104	7	0.5	21	1.5
105	7	0.75	14	1.5
106	3	0.25	24	2
107	3	0.5	12	2
108	3	0.75	8	2
109	4	0.25	32	2
110	4	0.5	16	2
111	4	0.75	10.7	2
112	5	0.25	40	2
113	5	0.5	20	2
114	5	0.75	13.3	2
115	6	0.25	48	2
116	6	0.5	24	2
117	6	0.75	16	2
118	7	0.25	56	2
119	7	0.5	28	2
120	7	0.75	18.7	2
121	3	0.25	48	4
122	3	0.5	24	4
123	3	0.75	16	4
124	4	0.25	64	4
125	4	0.5	32	4
126	4	0.75	21.3	4

127	5	0.25	80	4
128	5	0.5	40	4
129	5	0.75	26.7	4
130	6	0.25	96	4
131	6	0.5	48	4
132	6	0.75	32	4
133	7	0.25	112	4
134	7	0.5	56	4
135	7	0.75	37.3	4
Gains Certain Trials				
Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
1	3	1	0.8	0.25
2	4	1	1	0.25
3	5	1	1.3	0.25
4	6	1	1.5	0.25
5	7	1	1.8	0.25
6	3	1	1.5	0.5
7	4	1	2	0.5
8	5	1	2.5	0.5
9	7	1	3.5	0.5
10	3	1	2	0.66
11	4	1	2.6	0.66
12	5	1	3.3	0.66
13	7	1	4.6	0.66
14	3	1	2.4	0.8
15	4	1	3.2	0.8
16	6	1	4.8	0.8
17	7	1	5.6	0.8
18	3	1	3.8	1.25
19	4	1	5	1.25
20	5	1	6.3	1.25
21	6	1	7.5	1.25
22	7	1	8.8	1.25
23	3	1	4.5	1.5
24	4	1	6	1.5
25	5	1	7.5	1.5
26	6	1	9	1.5
27	7	1	10.5	1.5
28	3	1	6	2
29	4	1	8	2
30	5	1	10	2
31	6	1	12	2
32	7	1	14	2

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
33	3	1	12	4
34	4	1	16	4
35	5	1	20	4
36	6	1	24	4
37	7	1	28	4
Losses Risky Trials				
Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
1	-3	0.25	-3	0.25
2	-3	0.5	-1.5	0.25
3	-3	0.75	-1	0.25
4	-4	0.25	-4	0.25
5	-4	0.5	-2	0.25
6	-4	0.75	-1.3	0.25
7	-5	0.25	-5	0.25
8	-5	0.5	-2.5	0.25
9	-5	0.75	-1.7	0.25
10	-6	0.25	-6	0.25
11	-6	0.5	-3	0.25
12	-6	0.75	-2	0.25
13	-7	0.25	-7	0.25
14	-7	0.5	-3.5	0.25
15	-7	0.75	-2.3	0.25
16	-3	0.25	-6	0.5
17	-3	0.5	-3	0.5
18	-3	0.75	-2	0.5
19	-4	0.25	-8	0.5
20	-4	0.5	-4	0.5
21	-4	0.75	-2.7	0.5
22	-5	0.25	-10	0.5
23	-5	0.5	-5	0.5
24	-5	0.75	-3.3	0.5
25	-6	0.25	-12	0.5
26	-6	0.5	-6	0.5
27	-6	0.75	-4	0.5
28	-7	0.25	-14	0.5
29	-7	0.5	-7	0.5
30	-7	0.75	-4.7	0.5
31	-3	0.25	-7.9	0.66
32	-3	0.5	-4	0.66
33	-3	0.75	-2.6	0.66
34	-4	0.25	-10.6	0.66

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
35	-4	0.5	-5.3	0.66
36	-4	0.75	-3.5	0.66
37	-5	0.25	-13.2	0.66
38	-5	0.5	-6.6	0.66
39	-5	0.75	-4.4	0.66
40	-6	0.25	-15.8	0.66
41	-6	0.5	-7.9	0.66
42	-6	0.75	-5.3	0.66
43	-7	0.25	-18.5	0.66
44	-7	0.5	-9.2	0.66
45	-7	0.75	-6.2	0.66
46	-3	0.25	-9.6	0.8
47	-3	0.5	-4.8	0.8
48	-3	0.75	-3.2	0.8
49	-4	0.25	-12.8	0.8
50	-4	0.5	-6.4	0.8
51	-4	0.75	-4.3	0.8
52	-5	0.25	-16	0.8
53	-5	0.5	-8	0.8
54	-5	0.75	-5.3	0.8
55	-6	0.25	-19.2	0.8
56	-6	0.5	-9.6	0.8
57	-6	0.75	-6.4	0.8
58	-7	0.25	-22.4	0.8
59	-7	0.5	-11.2	0.8
60	-7	0.75	-7.5	0.8
61	-3	0.25	-12	1
62	-3	0.5	-6	1
63	-3	0.75	-4	1
64	-4	0.25	-16	1
65	-4	0.5	-8	1
66	-4	0.75	-5.3	1
67	-5	0.25	-20	1
68	-5	0.5	-10	1
69	-5	0.75	-6.7	1
70	-6	0.25	-24	1
71	-6	0.5	-12	1
72	-6	0.75	-8	1
73	-7	0.25	-28	1
74	-7	0.5	-14	1
75	-7	0.75	-9.3	1
76	-3	0.25	-15	1.25
77	-3	0.5	-7.5	1.25

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
78	-3	0.75	-5	1.25
79	-4	0.25	-20	1.25
80	-4	0.5	-10	1.25
81	-4	0.75	-6.7	1.25
82	-5	0.25	-25	1.25
83	-5	0.5	-12.5	1.25
84	-5	0.75	-8.3	1.25
85	-6	0.25	-30	1.25
86	-6	0.5	-15	1.25
87	-6	0.75	-10	1.25
88	-7	0.25	-35	1.25
89	-7	0.5	-17.5	1.25
90	-7	0.75	-11.7	1.25
91	-3	0.25	-18	1.5
92	-3	0.5	-9	1.5
93	-3	0.75	-6	1.5
94	-4	0.25	-24	1.5
95	-4	0.5	-12	1.5
96	-4	0.75	-8	1.5
97	-5	0.25	-30	1.5
98	-5	0.5	-15	1.5
99	-5	0.75	-10	1.5
100	-6	0.25	-36	1.5
101	-6	0.5	-18	1.5
102	-6	0.75	-12	1.5
103	-7	0.25	-42	1.5
104	-7	0.5	-21	1.5
105	-7	0.75	-14	1.5
106	-3	0.25	-24	2
107	-3	0.5	-12	2
108	-3	0.75	-8	2
109	-4	0.25	-32	2
110	-4	0.5	-16	2
111	-4	0.75	-10.7	2
112	-5	0.25	-40	2
113	-5	0.5	-20	2
114	-5	0.75	-13.3	2
115	-6	0.25	-48	2
116	-6	0.5	-24	2
117	-6	0.75	-16	2
118	-7	0.25	-56	2
119	-7	0.5	-28	2
120	-7	0.75	-18.7	2

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
121	-3	0.25	-48	4
122	-3	0.5	-24	4
123	-3	0.75	-16	4
124	-4	0.25	-64	4
125	-4	0.5	-32	4
126	-4	0.75	-21.3	4
127	-5	0.25	-80	4
128	-5	0.5	-40	4
129	-5	0.75	-26.7	4
130	-6	0.25	-96	4
131	-6	0.5	-48	4
132	-6	0.75	-32	4
133	-7	0.25	-112	4
134	-7	0.5	-56	4
135	-7	0.75	-37.3	4
Losses Certain Trials				
Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
1	-3	1	-0.75	0.25
2	-4	1	-1	0.25
3	-5	1	-1.25	0.25
4	-6	1	-1.5	0.25
5	-7	1	-1.75	0.25
6	-3	1	-1.5	0.5
7	-4	1	-2	0.5
8	-5	1	-2.5	0.5
9	-7	1	-3.5	0.5
10	-3	1	-1.98	0.66
11	-4	1	-2.64	0.66
12	-5	1	-3.3	0.66
13	-7	1	-4.62	0.66
14	-3	1	-2.4	0.8
15	-4	1	-3.2	0.8
16	-6	1	-4.8	0.8
17	-7	1	-5.6	0.8
18	-3	1	-3.75	1.25
19	-4	1	-5	1.25
20	-5	1	-6.25	1.25
21	-6	1	-7.5	1.25
22	-7	1	-8.75	1.25
23	-3	1	-4.5	1.5
24	-4	1	-6	1.5

Trial #	Certain Value ($)	pWIN (%)	Gamble Value ($)	rEV
25	-5	1	-7.5	1.5
26	-6	1	-9	1.5
27	-7	1	-10.5	1.5
28	-3	1	-6	2
29	-4	1	-8	2
30	-5	1	-10	2
31	-6	1	-12	2
32	-7	1	-14	2
33	-3	1	-12	4
34	-4	1	-16	4
35	-5	1	-20	4
36	-6	1	-24	4
37	-7	1	-28	4